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Public Sentiment toward Indonesia's Free Nutritious Meal Program on X: A Systematic Review

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ABSTRACT

This study regularly reviews research on public sentiment toward Indonesia's Free Nutritional Food (MBG) program expressed on X/Twitter. Using the PRISMA 2020 framework, literature published between 2024 and 2026 was identified through Google Scholar and GARUDA, resulting in 30 empirical studies included in the final review. The data were synthesized descriptively and narratively by examining sentiment patterns, recurring issues in public responses, and methodological variations across studies. The findings show that public sentiment toward MBG is heterogeneous. Positive sentiment was reported more frequently, but substantial negative, neutral, and polarized responses were also identified. Positive responses were mainly associated with expected nutritional and social benefits, while critical responses focused on implementation, distribution, food safety, budget management, transparency, and accountability. Differences in reported sentiment were also linked to variations in data-collection periods, dataset sizes, labeling procedures, classification models, preprocessing techniques, and sentiment categories. This review contributes a communication perspective by moving beyond algorithm performance to explain how MBG is discussed and evaluated within digital public discourse on X

INTRODUCTION

Indonesia's Free Nutritious Meal Program (MBG), or Free Nutritious Meal program, has become a major national initiative that has secured widespread public interest. Officially launched on January 6, 2025, it initially involved 190 units Service Nutrition Fulfillment (SPPG) and benefited around 570,000 individuals. By January 2026, the National Nutrition Agency reported 19,188 SPPGs across 38 provinces, serving approximately 55.1 million people. The rapid expansion of MBG has raised public awareness and triggered discussions concerning its implementation, benefits, distribution, quality, and accountability. Large public programs often elicit different reactions among citizens, who evaluate both policy intentions and their experiences with implementation (Ceron & Negri, 2016).

Social media provides a new medium for these responses, enabling their sharing, circulation, and contestation. Such platforms generate large volumes of user-generated content, allowing analysis of public discussions, opinions, and issues related to government programs through computational methods (Stieglitz et al., 2018; Rathore et al., 2017). X, formerly known as Twitter, is particularly useful because its text-focused, interactive format makes it suitable for studying popular sentiment and discussion on social and policy matters (Zimbra et al., 2018). Sentiment analysis classifies these texts into positive, negative, or neutral categories, helping identify patterns within extensive online conversations (Zimbra et al., 2018).

The prominence of MBG in online discussions has led to increased research into public attitudes on X. However, findings vary.Munir & Voutama (2025) analyzed 1,500 posts and found predominantly negative sentiment. Muhabbab et al. (2025), with a dataset of 7,958 posts, identified 3,752 positive, 3,358 neutral, and 848 negative posts. Sultoni et al. (2025), using 47,803 posts, reported 47.1% positive, 41.9% negative, and 11.0% neutral sentiment. These differences indicate that results depend on factors such as observation periods, dataset sizes, labeling methods, and analytical approaches, rather than showing a single, stable sentiment trend across all discussions on (Stieglitz et al., 2018)

Methodologies also vary widely in recent MBG sentiment research. Studies use approaches ranging from lexicon-based labeling and traditional machine-learning algorithms such as Naïve Bayes, Support Vector Machine, and Random Forest, to transformer models such as BERT and IndoBERT. For example, Sultoni et al. (2025) combined lexicon-based methods, TF-IDF, multiple classifiers, and topic modeling, while Muhabbab et al. (2025) compared IndoBERT using SVM. Variations in data collection, preprocessing, and analysis are critical because each step influences the patterns detected and their interpretation (Stieglitz et al., 2018). Therefore, differences in sentiment findings should not be viewed solely as changes in public attitudes but also as consequences of methodological choices.

A previous review by Mukhlisin et al. (2026), examining 18 studies from 2024 to 2026, focused on machine-learning model effectiveness, popular algorithms, classification correctness , and overall sentiment trends. Though informative, a different perspective from a communication standpoint is

necessary. It is important to understand what these results show about public communication around MBG, recurring sentiment patterns, and reasons for conflicting conclusions. Social media analysis sheds light on responses during policy processes though should be considered alongside the context in which online expressions occur (Ceron & Negri, 2016).

Caution is needed when interpreting sentiment from X, as expressions on the platform may not represent the entire Indonesian population. Users often differ regularly in demographics, political engagement, and communication behavior, although these differences vary across populations and platforms (Mellon & Prosser, 2017). According to this study, ' public attitude ' specifically refers to online expressions on X, not necessarily the total public opinion. This approach situations X as a digital space where attitudes, support, criticism, and concerns about MBG are visible, without assuming these online sentiments reflect all Indonesian citizens (Mellon & Prosser, 2017; Ceron & Negri, 2016).

Filling this gap, the current review thoroughly examines public attitude toward MBG on X. Unlike previous reviews focused mainly on machine-learning performance, this analysis adopts a communication perspective. It examines the direction of sentiment, the common issues raised, and the underlying methodological factors differences across studies. This is important because social media analytics give interpretation of how public issues are communicated and understood, but methodological distinctions must be acknowledged in interpreting digital data (Rathore et al., 2017; Stieglitz et al., 2018). The study attempts to answer three questions:

- RQ1. What patterns of positive, neutral, and negative sentiment are reported in studies using X/Twitter data?
- RQ2. What recurring issues are linked to public responses to MBG on X?
- RQ3. How do methodological differences explain variations in findings across studies?

LITERATURE REVIEW

The prominence of MBG in online discussions has led to increased research into public attitudes on X. However, findings vary.Munir & Voutama (2025) analyzed 1,500 posts and found predominantly negative sentiment. Muhabbab et al. (2025), with a dataset of 7,958 posts, identified 3,752 positive, 3,358 neutral, and 848 negative posts. Sultoni et al. (2025), using 47,803 posts, reported 47.1% positive, 41.9% negative, and 11.0% neutral sentiment. These differences indicate that results depend on factors such as observation periods, dataset sizes, labeling methods, and analytical approaches, rather than showing a single, stable sentiment trend across all discussions on (Stieglitz et al., 2018)

METHODOLOGY

This study conducted a systematic review of the literature to examine research on public attitudes toward Indonesia's Free Nutritional Eats (MBG) program on the X communication platform. The review followed the PRISMA 2020 guidelines to find, filter, assess eligibility, and include appropriate studies (Page et al., 2021). Searches were done through Google Scholar and GARUDA (Digital Reference Garba), focusing on national-level publications about MBG. The studies included were published from 2024 to 2026. Search terms in Indonesian and English included "Free Nutritional Food," "analysis sentiment," "sentiment analysis," "Twitter," and "social media X." The main search combinations were " Free Nutritious Meals" with "analysis sentiment" on Twitter, and "Free Nutritious Meals " with "sentiment analysis" on Twitter, as well as "Free Nutritious Meals" with "sentiment analysis" on Twitter, sentiment " on social media X. Additional searches were carried out in GARUDA using the same terms.

Studies were included when they met six criteria: they examined the Indonesian MBG program; analyzed public sentiment, opinion, or responses; used posts from X/Twitter as the source of communication data; constituted empirical research; reported identifiable sentiment-analysis methods or classification results; and provided accessible full texts published in Indonesian or English between 2024 and 2026. Studies were excluded when they discussed MBG without sentiment analysis, examined sentiment unrelated to MBG, used communication data exclusively from platforms other than X/Twitter, were duplicate publications, or contained of literature reviews, theses, news reports, editorials, and other non-empirical sources. Study selection was conducted manually through duplicate checking, title and abstract screening, relevance assessment, and full-text eligibility review. The detailed study selection results are presented in the PRISMA flow diagram in the Results section.

A structured extraction matrix was used to organize information from relevant studies. It included variables such as the authors and publication year, data collection period, number of analyzed X/Twitter posts, sentiment -labeling method, the analysis algorithm or model, and the proportions of positive, neutral, and negative sentiments, along with the dominant sentiment and key findings. Particular attention was paid to differences in data collection times, dataset sizes, labeling techniques, and analytical approaches, as these methodical variations could impact the reported general opinion toward MBG.

The evidence collected was reviewed using descriptive and narrative summaries rather than statistical meta-analysis due to significant differences among the studies in dataset details, sentiment classification methods, algorithms, and reporting styles. The review emphasized three key points: the general public's attitude toward MBG, common issues associated with positive, neutral, and negative responses, and methodological variations that could explain differences in study results. This review viewed sentiment analysis not

simply as a comparison of different computational techniques, but as a method to understand how people communicate about and discuss the MBG program on X in the digital space.

RESULT AND DISCUSSION

Study Selection and Characteristics of the Included Studies

The process of selecting studies is outlined in Figure 1. The initial search yielded 892 records, consisting of 803 from Google Scholar and 89 from GARUDA. After removing 622 duplicate entries, 270 records remained for title and abstract screening. At this stage, 180 records were excluded because they were not aligned with the review's focus, leaving 90 records for further relevance and alignment assessment. An additional 40 records were excluded, resulting in 50 articles subjected to full-text eligibility review. Following this evaluation, 20 articles were excluded for not meeting the predefined inclusion criteria. Ultimately, 30 studies were included in the final systematic review. This sequential reduction demonstrates that the initial search strategy was intentionally broad, with subsequent screening stages narrowing the scope to empirical studies explicitly analyzing community sentiment toward the MBG program through communication on X/Twitter.

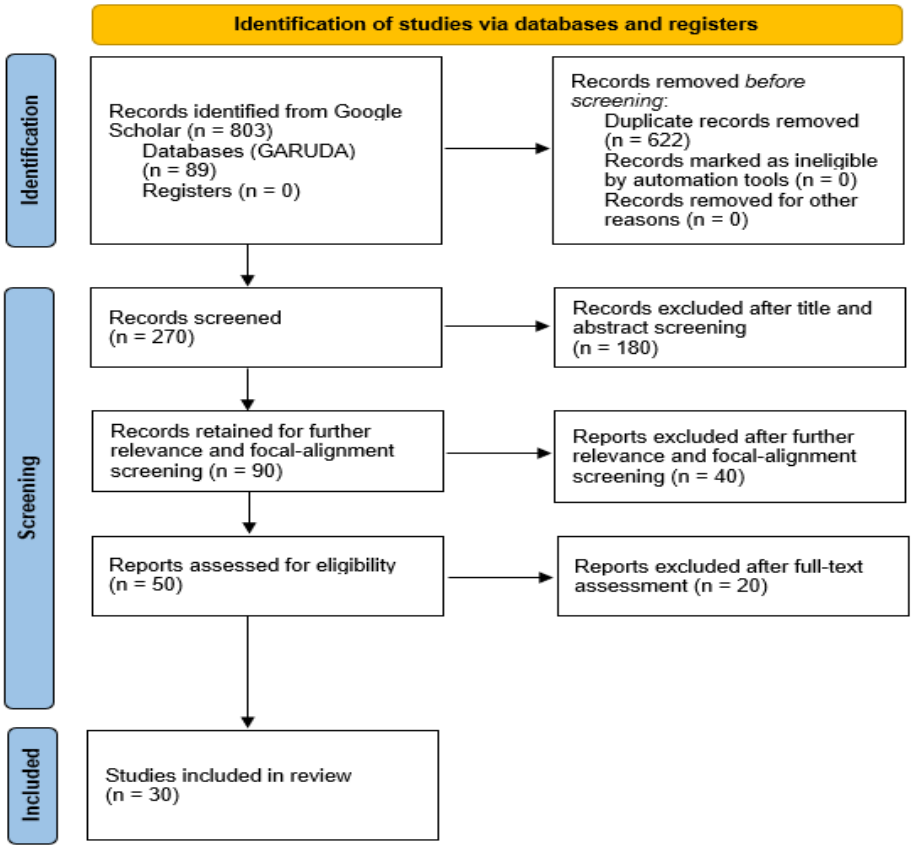

Figure 1. PRISMA Flow Diagrams

The final corpus consisted of 30 empirical studies published between 2025 and 2026, as presented in Table 1. Twelve studies (40%) were published in 2025, whereas 18 studies (60%) were published in 2026. This distribution signifies a rapid increase in scholarly attention to MBG-related sentiment analysis within a relatively short publication period. The concentration of studies in 2026 is

particularly noteworthy because more than half of the reviewed articles appeared in that year, indicating that investigating the feelings expressed about MBG on X has become an increasingly popular area of study following the implementation and increasing public visibility of the program. Table 1 also shows that the studies were strongly oriented toward computational analysis of digitally expressed public responses, although they differed substantially in the analytical techniques employed.

Table 1. Studies Included in the Systematic Literature Review

No.	Authors (Year)	Article Title	Main Method	DOI
1	Triningsih (2025)	Analysis Sentiment Regarding the Free Nutritional Meal Program Using Machine Learning Algorithms on Social Media X	Machine learning	10.47065/bits.v6i4.6534
2	Hermansyah & Hasibuan (2025)	Sentiment Analysis of Free Nutritious Meal Program on Social Media X using Linear Regression and Random Forest Algorithms	Linear Regression, Random Forest	10.33558/pixel.v13i1.10633
3	Ainur et al. (2025)	Analysis Public Sentiment Towards the Free Nutritional Meal Program Using the Random Forest Method on Platform X	Random Forest, TF-IDF	10.24176/sitech.v8i1.15628
4	Ati & Prasetyaningrum (2025)	Analysis of Community Sentiment Towards Free Nutrition Meal Programs on Twitter Using Naïve Bayes, Support Vector Machine, K-Nearest Neighbors, and Ensemble Methods	NB, SVM, KNN, Ensemble	10.51519/journalisi.v7i2.1098
5	Munir & Voutama (2025)	Analysis Sentiment Tweets on Social Media X About the Free Nutritional Meal Program Using the NLP Method	K-Means, SVM, BERT	10.23960/jitet.v13i3.6912
6	Arif & Kustiyono (2025)	Analysis Sentiment Free Nutritious Meal Policy on Social Media Using Python TextBlob -Based Natural Language Processing in Indonesia	TextBlob /NLP	10.52436/1.jpti.931
7	Fatkhurrohman et al. (2025)	Analysis Sentiment of the Indonesian Government's Free Nutritious Meal	SVM, TF-IDF	10.31004/riggs.v4i3.2533

No.	Authors (Year)	Article Title	Main Method	DOI
		Program Through Twitter Using the SVM Method		
8	Ramadhan & Khoirunnisa (2025)	An Integrated Random Forest for Analyzing Public Sentiment on the " Free Nutritious Meals" Program	RF, AdaBoost, XGBoost , Bagging, Stacking	10.51519/journalisi.v7i3.1184
9	Sultoni et al. (2025)	Public Sentiment Analysis and Distribution Optimization of Indonesia's Free Nutritious Meals (MBG) Program	SVM, BERT, LDA, clustering	10.22146/jmt.108835
10	Muhabbab et al. (2025)	Sentiment Analysis of Indonesia's Free Nutritious Meal Program on Platform X (Formerly Twitter) Using IndoBERT	IndoBERT , SVM	10.30829/zero.v9i3.27629
11	Sulistyo & Setiadi (2025)	Analysis Sentiment Free Nutritious Meal Policy Using IndoBERT and Machine Learning	IndoBERT , RF, XGBoost , Ensemble	10.37859/jf.v15i3.10546
12	Subarkah (2025)	Sentiment Perspective of Government's Free Nutritious Meal Policy on Social Media	IndoBERT , Bi-LSTM	10.37802/joti.v7i2.1065
13	Silaban et al. (2026)	Public Sentiment Analysis of Free Nutritious Meal Program Discourse on Social Media X Using Support Vector Machine N-Gram Features Based	SVM, N-Gram, TF-IDF	10.31253/te.v9i2.4355
14	Manao & Mujiyono (2026)	Sentiment Analysis of the Free Nutritious Meal Program on Twitter Using Naive Bayes and IndoBERT -Based Labeling	Naïve Bayes, Linear SVC, IndoBERT	10.63158/journalisi.v8i1.1345
15	Prianto et al. (2026)	Comparative Performance Analysis of Random Forest and Logistic Regression for Sentiment Classification of the Makan Bergizi Gratis Program on Platform	RF, Logistic Regression	10.63158/journalisi.v8i1.1371
16	Pratama et al. (2026)	Analysis Sentiment on Free Nutritious Meals on Social Media X Using the	Decision Tree, Naive Bayes	10.36040/jati.v9i6.15525

No.	Authors (Year)	Article Title	Main Method	DOI
		Decision Tree Method with Naive Bayes Comparator		
17	Haerani (2026)	Analysis Free Nutritional Meal Program Sentiment Based on Comments on Social Media X Using GRU	GRU/RNN	
18	Putri & Novianto (2026)	Analysis Indonesian Public Sentiment towards the Free Nutritious Meal Program (MBG) on Social Media X Using Comparison Naive Bayes Algorithm and Support Vector Machine	NB, SVM	10.36040/jati.v10i3.18441
19	Ilham & Kartikadarma (2026)	Sentiment Analysis of Free Nutritious Meal Program on Platform X: Comparing Naive Bayes, SVM, Random Forest, and IndoBERT	NB, SVM, RF, IndoBERT	10.30871/jaic.v10i3.12959
20	Mursyid et al. (2026)	Implementation of IndoBERT in Sentiment Analysis of Free Nutritious Meal Programs on the X Social Media Platform	IndoBERT	10.24036/jtip.v19i1.1104
21	Chandra & Dewi (2026)	Analysis Sentiment On the Free Nutritious Meal Program on Social Media X Using the Naive Bayes Classifier Method	Naive Bayes, SMOTE	10.24036/w6zjmv19
22	Wulandari et al. (2026)	Analysis Twitter Social Media Community Sentiment Towards the Free Nutritious Meal Program Using IndoBERT and DistilBERT	IndoBERT , DistilBERT	10.47970/siskom-kb.v9i3.904
23	Wibowo et al. (2026)	Analysis Sentiment Multiclass Free Nutritious Meal Program on Social Media X Using VaderSentiment and SMOTE Oversampling Based SVM	VADER, SVM, SMOTE	10.47065/bulletinds.v5i3.10323
24	Hashim (2026)	Sentiment Analysis of Indonesia's Free Nutritious Meal Program on X Posts	SVM, Random Forest	10.18860/cauchy.v11i1.40717

No.	Authors (Year)	Article Title	Main Method	DOI
		Using SVM and Random Forest		
25	Sari (2026)	Sentiment Analysis of the Free Nutritious Meal or Free Nutritious Meal (MBG) Program on Social Media	VADER + qualitative interpretation	10.55942/pssj.v6i6.2023
26	Ihdahayuningsih (2026)	Analysis Public Sentiment Towards the Free Nutritional Meal Program on Social Media X Using Naive Bayes	Naive Bayes	10.62357/jsit.v5i1.929
27	Ariani et al. (2026)	Evaluation Comparative Deep Machine Learning Algorithms Analysis Sentiment on Social Media About the Free Nutritional Meal Program X	NB, KNN, SVM, DT, RF, LR	10.30865/jurikom.v13i3.9741
28	Farizi et al. (2026)	Analysis Sentiment of the Free Nutritious Meal Program on Social Media X with Support Vector Machine Algorithm	SVM, TF-IDF	10.23960/jitet.v14i3.10195
29	Retnosari et al. (2026)	Comparison of Naïve Bayes and Support Vector Machine Methods in Analysis Sentiment of the Free Nutritional Meal Program on Social Media X	NB, SVM	10.36040/jati.v10i4.18689
30	Alkadri et al. (2026)	Sentiment Analysis of X Users' Opinions on the Free Nutritious Meal (MBG) Program Using Support Vector Machine	SVM, hybrid labeling	10.66314/joresd.v4i1.1094

The range of methods used in the studies reviewed shows a lot of variation. Support Vector Machine (SVM) was the most common approach, appearing either as the main classifier or as a comparison model in 14 out of 30 studies. Naïve Bayes was used in nine studies, and Random Forest in eight. Transformer-based methods are becoming more popular, with IndoBERT featured in seven studies, often alongside traditional machine learning techniques. Other methods include BERT, KNN, Decision Tree, Logistic Regression, and XGBoost , as well as tools like TextBlob , VADER, GRU, Bi-LSTM, and DistilBERT . Some studies combined ensemble learning and hybrid labeling. Techniques such as TF-IDF, N-Gram features, SMOTE, topic modeling, and clustering were also used in several investigations. This variety of

approaches shows that research doesn't depend on a single method but instead blends lexicon-based techniques, traditional machine learning, deep learning, and transformer models.

A clear trend over time is evident. Earlier studies from 2025 used traditional classifiers and newer methods, such as Random Forest, SVM, TextBlob, BERT, IndoBERT, and Bi-LSTM. By 2026, research expanded these approaches, incorporating GRU, DistilBERT, VADER-based labeling, oversampling with SMOTE, hybrid strategies, and direct comparisons of multiple classifiers. The variation in models highlights the importance of context when interpreting results, as different classification techniques, labeling methods, and analysis setups can affect reported sentiment patterns. Therefore, this review doesn't focus solely on which classifier performs best. Instead, it emphasizes understanding these methodological differences to better interpret the patterns in public sentiment, communication challenges, and the variations among study findings, which are discussed in the upcoming sections guided by specific research questions.

Patterns of Public Sentiment toward the MBG Program on

The analysis of the 30 studies shows that public opinion on the Free Nutritional Food (MBG) program on X is mixed, rather than clearly positive or negative. Twelve studies with explicit sentiment data indicate mostly positive feelings, eight lean toward negativity, one highlights neutrality as the dominant view, and another reveals a mix of negative and neutral responses. Other studies, which focused on classifier performance, reported positive, neutral, and negative responses but did not provide clear sentiment distributions. This suggests that the existing research does not present a definitive picture of public reaction to MBG; instead, different datasets reveal a variety of attitudes—supportive, critical, neutral, or ambivalent.

Most studies found that positive sentiment was the dominant trend. Fatkhurrohman et al. (2025) reported 71.5% positive responses, with 15.8% negative and 12.6% neutral. Similarly, Silaban et al. (2026) analyzed 931 posts, of which 683 (73.36%) were positive and 248 (26.64%) negative. Prianto et al. (2026) showed an even stronger positivity, with 95.3% of 1,002 posts categorized as positive, while Putri and Novianto (2026) found about 90% of 3,457 posts to be positive. Sari (2026) identified 2,324 positive posts out of 2,774 relevant ones, with only 303 neutral and 147 negative. Alkadri et al. (2026) reported a less extreme but still positive-majority distribution: 50.42% positive, 38.55% negative, and 11.03% neutral.

Positive dominance, however, should not always be seen as overwhelming agreement. Several extensive datasets revealed a more polarized communication landscape. Sultoni et al. (2025), analyzing 47,803 X posts, found 47.1% positive, 41.9% negative, and 11.0% neutral sentiment. Similarly, Hasyim et al. (2026) reported a comparable distribution of 7,452 tweets, with 47.62% positive, 39.80% negative, and 12.57% neutral sentiments. Although positive sentiment was the largest category in both studies, the small difference between positive and negative expressions suggests a significant presence of both support

and criticism rather than an uncontested positive response. Chandra and Dewi (2026) also observed only a slight difference between 407 positive and 383 negative comments, with another 304 classified as neutral.

Other studies show a contrasting trend where negative or critical communication prevails. Arif and Kustiyono (2025) reported that 71.8% of 657 tweets were negative, with only 18.6% positive and 9.6% neutral. Sulistyo and Setiadi (2025), analyzing a larger dataset of 12,389 posts, found 68.6% negative sentiment, compared to 19.5% positive and 11.9% neutral responses. Munir and Voutama (2025) also identified negative sentiment as the dominant category among 1,500 posts. Recent research supports this pattern: Ilham and Kartikadarma (2026) classified 1,113 of 1,906 tweets as negative and 793 as positive, while Mursyid et al. (2026) reported 42.71% negative, 30.85% neutral, and 26.43% positive sentiments. Farizi et al. (2026) and Ihdahayuningsih et al. (2026) similarly found their datasets inclined toward negative responses.

The corpus reveals that neutrality and mixed sentiments are significant patterns rather than just residual categories. Ariani et al. (2026) observed that 66.3% of 2,000 posts were neutral, with 22.6% negative and only 11.1% positive. This distribution notably differs from studies highlighting strong positive or negative dominance, indicating that much of X communication may be informational, descriptive, or non-evaluative. Similarly, Manao and Mujiyono (2026) found that negative and neutral opinions were prevalent under IndoBERT -based labeling, demonstrating that a binary view of MBG discourse, misses a substantial part of online communication.

Differences in sentiment direction are also evident among studies that utilize relatively large datasets. Muhabbab et al. (2025), analyzing 7,958 manually annotated posts, found 3,752 positive, 3,358 neutral, and 848 negative posts, showing a tendency toward positivity with a significant neutral portion. conversely, Mursyid et al. (2026), examining 3,643 processed posts, identified negative sentiment as the most common. Hashim et al. (2026), with 7,452 tweets, exhibited a nearly balanced distribution of positive and negative posts, while Sari (2026), with 2,774 relevant posts, observed a strong positive majority. These divergent results from datasets of several thousand posts suggest that sample size alone does not account for variations in sentiment patterns.

Instead, each distribution captures communication within a specific dataset, period, 2343abelling process, and analysis method. These differences underpin the subsequent examination of recurring themes in positive, negative, and neutral responses, along with the methodological factors that might cause discrepancies across studies.

Recurring Issues in Public Responses toward MBG on

The review reveals that discussions about the Free Nutritional Eats (MBG) program on X extends beyond simple support or opposition. In studies that went beyond sentiment analysis to include topic-level insights, word-frequency analysis, topic modeling, or qualitative discussion, public responses consistently highlighted expected benefits, implementation quality, food safety, distribution, budget oversight, and government accountability. Not all of the 30 studies included reported detailed thematic findings; some mainly focused on classifier performance. As a result, this thematic synthesis is based on studies that explicitly addressed the substantive content behind positive, negative, or neutral sentiments.

The dominant theme was how people perceived the nutritional and social value of the program. Positive feedback frequently connected MBG to improved child nutrition, wider meal access, support for vulnerable groups, and efforts to tackle nutritional problems. Sari (2026) observed that the most favorable discussions focused on children, nutrition, stunting reduction, and program endorsement. Likewise, Sultoni et al. (2025) emphasizes maternal and child health as central to MBG-related conversations. These findings imply that many supporters primarily see MBG as offering social advantages. Instead of merely distributing food, the program was viewed as a government initiative aimed at enhancing children's well-being and nutrition. In this context, optimistic attitudes were often driven by anticipated benefits rather than detailed technical aspects (Sultoni et al., 2025; Sari, 2026).

Meanwhile, public responses often shifted focus from the program's goals to concerns about implementation, distribution, and equitable access. Support for free nutritious meals did not always lead to confidence in how the program was carried out. Several studies revealed that users questioned whether meals would be distributed fairly, if all eligible recipients would receive the same quality of service, and whether the program could reach different regions equally. For example, Sultoni et al. (2025) highlighted access inequality as a key issue in negative feedback, noting that geographical and socio-economic differences fueled public concern. Similarly, Fatkhurrohman et al. (2025) reported critical responses about the program's readiness and distribution. This pattern indicates that public communication on X often distinguishes between support for MBG's purpose and critiques of its implementation. Users can agree with the goal of improving nutrition but remains critical of the program's operational capacity.

Concerns about food quality and safety became particularly significant as MBG moved from policy discussions to everyday practice. Several studies linked negative sentiments to reports on food quality, hygiene, and suspected food poisoning. Sari (2026) noted that negative talks involved worries about food safety and poisoning cases, while Ihdahayuningsih et al. (2026) also tied unfavorable responses to complaints about issues faced after eating MBG meals. These discussions are crucial because they illustrate how public opinion shifts once the program is experienced firsthand or when incidents are highlighted on social media. Users no longer assess just the promise of nutritious

meals but also scrutinize their safety, hygiene, appropriateness, and consistent preparation. As a result, food safety becomes a highly sensitive issue, where a single failure can severely impact the program's overall credibility.

Another recurring theme focused on budget allocation, transparency, and accountability. Since MBG is a large public program, discussions on X also covered how public funds are used, whether the budget aligns with the program's benefits, and how monitoring is conducted. Sultoni et al. (2025) highlighted transparency as a key issue in negative discourse. Similarly, Sari (2026) found criticism around budget priorities, accountability, procurement, and supplier responsibility. Fatkhurrohman et al. (2025) pointed out public concerns regarding the financial aspects of implementation. These findings show that attitudes toward MBG are influenced partly by users' perceptions of its governance. While many appreciate its nutritional goals, there are also calls for more transparency about spending, procurement, monitoring, and accountability, especially when implementation issues arise.

Public responses also revealed political and economic interpretations of MBG. Some discussions link the program to political motives, government performance, redistribution, local economic actors, and state legitimacy. Fatkhurrohman et al. (2025) noted that some critical comments were tied to suspicion about the political implications of the program. Sari (2026) further indicated that MBG discussions included questions about redistribution, local supply chains, procurement, micro and small enterprises, and the broader political economy. This suggests that MBG was viewed beyond just a nutrition policy. For some users, it also served as a way to assess government priorities, public resource distribution, and the connection between policy implementation and beneficiaries. Positive reactions may indicate confidence in visible welfare efforts, while negative ones could reflect concerns about political motives, procurement issues, or inefficiencies.

A common pattern in the reviewed studies is that support and criticism often appear together. For example, Sultoni et al. (2025) noted a fairly balanced sentiment distribution, suggesting that positive and negative opinions often focus on different aspects of the same program. A user might agree with the importance of nutritious meals for children but criticize issues like food quality, distribution, or budget. This explains why some datasets show polarization rather than a clear majority opinion. Therefore, mixed responses should not be viewed as inconsistent public opinion; instead, they likely reflect the multidimensional nature of MBG. Different aspects of the program trigger various evaluations, and X provides a space where these assessments can coexist.

Neutral responses should not be overlooked, as they do not necessarily indicate indifference. In some research, neutral posts involve sharing information, circulating news, describing implementations, or engaging in discussions without explicit evaluation. This is particularly important because the high proportion of neutral content in certain datasets may reflect X's informational role as well as its function as a platform for expressing opinions. For example, Ariani et al. (2026) identified neutral sentiment as the most prevalent category in their dataset. These results imply that conversations about

MBG encompass both evaluative and informational exchanges. Therefore, 2346abelling all neutral responses as just lack of engagement could oversimplify the complex communication patterns related to the program.

Methodological Variations Explaining Differences in Sentiment Findings

The 30 reviewed studies reveal significant methodological differences in how public sentiment toward MBG was identified and classified. These variations encompass not only the choice of algorithms but also extend to data collection, dataset size, labeling procedures, text representation, class structure, and preprocessing methods. Such differences are crucial because social media analysis involves multiple stages, from data discovery and collection to preparation and analysis and variations at each stage can affect the patterns that are ultimately reported (Stieglitz et al., 2018).

A key source of variation lies in the dataset and the period when the data was collected. The included studies examined vastly different volumes of X posts, from a few hundred to tens of thousands. Some utilized smaller datasets, while others, like Sultoni et al. (2025), analyzed a much larger corpus. Varying collection periods also mean that the studies captured different stages in the MBG program's development. Posts from early policy discussions may reflect expectations and political debates, whereas data from after implementation likely focus more on distribution, food quality, or incidents related to the program. As a result, differences in sentiment outcomes might partly arise from the varying communication contexts of each dataset captured, not solely from differences in public attitudes.

The studies also varied significantly in their sentiment-labeling methods. Some employed lexicon-based tools like TextBlob or VADER, while others used manual annotation, machine-assisted labeling, IndoBERT -based methods, or hybrid techniques. For example, Arif and Kustiyono (2025) utilized TextBlob, whereas Manao and Mujiyono (2026) adopted IndoBERT -based labeling. Wibowo et al. (2026) combined VADER with SVM and SMOTE, while Alkadri et al. (2026) implemented a hybrid approach. These differences in labeling strategies impact how posts that are ambiguous, ironic, or context-dependent are classified as positive, neutral, or negative, highlighting a known challenge in Twitter sentiment analysis (Zimbra et al., 2018).

The selection of classification models represented another significant difference. Traditional machine-learning techniques such as Naïve Bayes, Support Vector Machine, Random Forest, Decision Tree, K-Nearest Neighbors, and Logistic Regression are common, while newer research increasingly adopted deep learning and transformer-based models such as GRU, Bi-LSTM, BERT, IndoBERT, and DistilBERT. Some studies relied on a single model; others compared multiple algorithms or used ensemble methods. Due to differences in how these approaches encode language and context, the same or similar posts might not always be classified consistently across models. Zimbra et al. (2018) also found that Twitter sentiment analysis systems can perform differently depending on the dataset, and classification errors remain a key challenge.

Variation was also observed in how texts were represented and preprocessed. Several studies employed TF-IDF, N-Gram features, oversampling

via SMOTE, or combinations of these methods, while others utilized contextual embeddings from BERT-based models. For example, Ainur et al. (2025) and Fatkhurrohman et al. (2025) used TF-IDF; Silaban et al. (2026) combined SVM with N-Gram and TF-IDF; and Chandra and Dewi (2026) applied SMOTE to address class imbalance. These methodological choices influence the weighting of linguistic patterns and the representation of minority sentiment classes in the final classification. The number of sentiment categories also varied across studies. Most used three categories—positive, neutral, and negative—while some employed binary classifications or focused mainly on positive and negative sentiments. This variation complicates direct comparisons, as a post deemed neutral in a three-class system might be categorized as positive or negative in a binary model. Therefore, comparing the reported percentages of dominant sentiment across studies requires considering the classification structure used.

CONCLUSIONS AND RECOMMENDATIONS

This systematic review shows that public sentiment toward Indonesia's Free Nutritional Food (MBG) program on X cannot be characterized by a single pattern. Across the 30 reviewed studies, positive sentiment was reported more frequently, but substantial negative, neutral, and polarized responses were also found. These differences reflect the multidimensional nature of public communication surrounding MBG. Positive responses were mainly associated with expected nutritional and social benefits, while critical responses focused on implementation, distribution, food safety, budget management, transparency, and accountability. The findings therefore suggest that sentiment toward MBG should be understood not simply as approval or rejection, but as a combination of public expectations and evaluations of how the program is implemented. The main contribution of this review is to shift attention from comparing the accuracy of sentiment-classification algorithms toward understanding what accumulated sentiment studies reveal about digital public communication surrounding MBG.

The review indicates that differences between studies are mainly affected by methodological choices such as data collection timing, dataset size, labeling methods, classification models, preprocessing, and sentiment class structures. Consequently, sentiment percentages from individual studies should not be seen as directly comparable or fully reflective of Indonesian public opinion. A key strength of this review is its synthesis of findings from the fast-growing field of MBG sentiment research within a communication framework. However, its limitations include the heterogeneity of included studies and the fact that some articles mainly focus on classifier performance without detailed thematic analysis. Future research should adopt more transparent and comparable data collection and labeling strategies, combine sentiment analysis with topic or discourse analysis, and study public communication changes during different phases of MBG implementation. These strategies would enhance understanding of how public responses to large-scale government initiatives evolve within digital communication environments.

REFERENCES

Ainur, Latifah, & Nugraha. (2025). Analisis Sentimen Publik Terhadap Program Makan Bergizi Gratis Menggunakan Metode Random Forest Pada Platform X. https://doi.org/10.24176/sitech.v8i1.15628

Alkadri, Rhendy, & Insani. (2026). Sentiment Analysis of X Users' Opinions on the Free Nutritious Meal (MBG) Program Using Support Vector Machine. https://doi.org/10.66314/joresd.v4i1.1094

Ariani, Norhikmah, & Pristyanto. (2026). Evaluasi Komparatif Algoritma Machine Learning dalam Analisis Sentimen Program Makan Bergizi Gratis di Media Sosial X. https://doi.org/10.30865/jurikom.v13i3.9741

Arif, & Kustiyono. (2025). Analisis Sentimen Kebijakan Makan Bergizi Gratis di Media Sosial Menggunakan Natural Language Processing Berbasis Python TextBlob di Indonesia. https://doi.org/10.52436/1.jpti.931

Ati, & Prasetyaningrum. (2025). Analysis of Community Sentiment Towards Free Nutrition Meal Programs on Twitter Using Naïve Bayes, Support Vector Machine, K-Nearest Neighbors, and Ensemble Methods. https://doi.org/10.51519/journalisi.v7i2.1098

Ceron, A., & Negri, F. (2016). The "Social Side" of Public Policy: Monitoring Online Public Opinion and Its Mobilization During the Policy Cycle. Policy & Internet, 8(2), 131–147. https://doi.org/10.1002/poi3.117

Chandra, & Dewi. (2026). Analisis Sentimen Terhadap Program Makan Bergizi Gratis Pada Media Sosial X Menggunakan Metode Naive Bayes Classifier. https://doi.org/10.24036/w6zjmv19

Farizi, Hendriadi, & Ridha. (2026). Analisis Sentimen Program Makan Bergizi Gratis pada Media Sosial X dengan Algoritma Support Vector Machine. https://doi.org/10.23960/jitet.v14i3.10195

Fatkhurrohman, Nugroho, & Fadillah. (2025). Analisis Sentimen Program Makan Bergizi Gratis Pemerintah RI Melalui Twitter Menggunakan Metode SVM. https://doi.org/10.31004/riggs.v4i3.2533

Haerani. (2026). Analisis Sentimen Program Makan Bergizi Gratis Berdasarkan Komentar di Media Sosial X Menggunakan GRU. https://doi.org/10.23960/jitet.v14i1.8754

Hasyim. (2026). Sentiment Analysis of Indonesia's Free Nutritious Meal Program on X Posts Using SVM and Random Forest. https://doi.org/10.18860/cauchy.v11i1.40717

Hermansyah, & Hasibuan. (2025). Sentiment Analysis of Free Nutritious Meal Programme on Social Media X using Linear Regression and Random Forest Algorithms. https://doi.org/10.33558/piksel.v13i1.10633

Ihdahayuningsih. (2026). Analisis Sentimen Masyarakat Terhadap Program Makan Bergizi Gratis Pada Media Sosial X Dengan Naïve Bayes. https://doi.org/10.62357/jsit.v5i1.929

Ilham, & Kartikadarma. (2026). Sentiment Analysis of Free Nutritious Meal Program on Platform X: Comparing Naive Bayes, SVM, Random Forest, and IndoBERT. https://doi.org/10.30871/jaic.v10i3.12959

Manao, & Mujiyono. (2026). Sentiment Analysis of the Free Nutritious Meal Program on Twitter Using Naive Bayes and IndoBERT-Based Labeling. https://doi.org/10.63158/journalisi.v8i1.1345

Mellon, J., & Prosser, C. (2017). Twitter and Facebook are not representative of the general population: Political attitudes and demographics of British social media users. Research & Politics, 4(3), 1–9. https://doi.org/10.1177/2053168017720008

Muhabbab, Bunyamin, & Hasmawati. (2025). Sentiment Analysis of Indonesia's Free Nutritious Meal Program on Platform X (Formerly Twitter) Using IndoBERT. https://doi.org/10.30829/zero.v9i3.27629

Mukhlisin, M., Berlilana, B., & Saputro, R. E. (2026). Literature Review: Comparison of Machine Learning Algorithms for Sentiment Analysis of Free Nutritious Meals. SISTEMASI: Jurnal Sistem Informasi, 15(3), 1110–1120. https://doi.org/10.32520/stmsi.v15i3.6201

Munir, R. A., & Voutama, A. (2025). Analisis Sentimen Cuitan di Media Sosial X Tentang Program Makan Bergizi Gratis dengan Metode NLP. Jurnal Informatika Dan Teknik Elektro Terapan, 13(3). https://doi.org/10.23960/jitet.v13i3.6912

Mursyid, Setiawan, & Arifin. (2026). Implementation of IndoBERT in Sentiment Analysis of Free Nutritious Meal Programs on the X Social Media Platform. https://doi.org/10.24036/jtip.v19i1.1104

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Pratama, Achmadi, & Sari. (2026). Analisis Sentimen terhadap Makan Bergizi Gratis pada Sosial Media X Menggunakan Metode Decision Tree dengan Pembanding Naive Bayes. https://doi.org/10.36040/jati.v9i6.15525

Prianto, Berlilana, & Saputro. (2026). Comparative Performance Analysis of Random Forest and Logistic Regression for Sentiment Classification of the Makan Bergizi Gratis Program on Platform X. https://doi.org/10.63158/journalisi.v8i1.1371

Putri, & Novianto. (2026). Analisis Sentimen Masyarakat Indonesia terhadap Program Makan Bergizi Gratis (MBG) di Media Sosial X Menggunakan Perbandingan Algoritma Naive Bayes dan Support Vector Machine. https://doi.org/10.36040/jati.v10i3.18441

Ramadhan, & Khoirunnisa. (2025). An Integrated Random Forest for Analyzing Public Sentiment on the "Makan Bergizi Gratis" Program. https://doi.org/10.51519/journalisi.v7i3.1184

Rathore, A. K., Kar, A. K., & Ilavarasan, P. V. (2017). Social Media Analytics: Literature Review and Directions for Future Research. Decision Analysis, 14(4), 229–249. https://doi.org/10.1287/deca.2017.0355

Retnosari, Hartanti, & Sari. (2026). Perbandingan Metode Naïve Bayes dan Support Vector Machine dalam Analisis Sentimen Program Makan Bergizi Gratis pada Media Sosial X. https://doi.org/10.36040/jati.v10i4.18689

Sari. (2026). Sentiment Analysis of the Free Nutritious Meal or Makan Bergizi Gratis (MBG) Program on Social Media X from the Perspective of the Political Economy of Development. https://doi.org/10.55942/pssj.v6i6.2023

Silaban, Simatupang, & Sipayung. (2026). Public Sentiment Analysis of Free Nutritious Meal Program Discourse on Social Media X Using Support Vector Machine N-Gram Features Based. https://doi.org/10.31253/te.v9i2.4355

Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics – Challenges in topic discovery, data collection, and data preparation. International Journal of Information Management, 39, 156–168. https://doi.org/10.1016/j.ijinfomgt.2017.12.002

Subarkah. (2025). Sentiment Perspective of Government's Free Nutritious Meal Policy on Social Media X using Indo-BERT and Bi-LTSM. https://doi.org/10.37802/joti.v7i2.1065

Sulistyo, & Setiadi. (2025). Analisis Sentimen Kebijakan Makan Bergizi Gratis Menggunakan IndoBERT dan Machine Learning. https://doi.org/10.37859/jf.v15i3.10546

Sultoni, A., Putra, D. A., Wahidah, H. N., Arief, M. M., R.M., P. J. P., & Utami, S. B. (2025). Public Sentiment Analysis and Distribution Optimization of Indonesia's Makan Bergizi Gratis (MBG) Program. Jurnal Matematika Thales, 7(1). https://doi.org/10.22146/jmt.108835

Triningsih. (2025). Analisis Sentimen Terhadap Program Makan Bergizi Gratis Menggunakan Algoritma Machine Learning Pada Sosial Media X. https://doi.org/10.47065/bits.v6i4.6534

Wibowo, Fatchan, & Supriyanto. (2026). Analisis Sentimen Multikelas Program Makan Bergizi Gratis di Media Sosial X Menggunakan VaderSentiment dan SVM Berbasis Oversampling SMOTE. https://doi.org/10.47065/bulletinds.v5i3.10323

Wulandari, Musyafa, & Wiharjo. (2026). Analisis Sentimen Masyarakat Media Sosial Twitter Terhadap Program Makan Bergizi Gratis Menggunakan IndoBERT dan DistilBERT. https://doi.org/10.47970/siskom-kb.v9i3.904

Zimbra, D., Abbasi, A., Zeng, D., & Chen, H. (2018). The state-of-the-art in Twitter sentiment analysis: A review and benchmark evaluation. ACM Transactions on Management Information Systems, 9(2), 5. https://doi.org/10.1145/3185045