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Food Communication Sentiment Analysis on Free Nutritious Meal Program: From Negative Bias to Policy Legitimacy

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Abstract Digital transformation has made social media a key platform for shaping food policy opinions. The Free Nutritious Meal (Makan Bergizi Gratis/MBG) program faces intense public debate online. This study aims to analyze public sentiment, map communication networks, and understand the construction of digital narratives surrounding MBG. This study uses a convergent parallel mixed methods that integrates quantitative and qualitative analysis simultaneously. A mixed-methods was employed through machine learning-based sentiment analysis, social network analysis, and qualitative thematic analysis. A sample of 87,589 mentions on Twitter (April–Aug 2025)) was validated through manual labeling (n = 1,200). This analysis was dissected using the theory of food communication to explain public acceptance of MBG's message construction on social media X and digital literacy theory that plays a role in reducing negative sentiment. Results show that 55.7% of mentions were negative, 43.3% were positive, and the remaining 1% were neutral. There was a spike in conversation in May 2025, with a fragmented network (modularity ≈ 0.41), and impressions were concentrated on a few influencers. Qualitative analysis identified negative framing (politicization, doubts about effectiveness) and positive framing (nutritional benefits, equity). These findings underscore the need for evidence-based communication strategies, including real-time monitoring, engagement with verified influencers, and strengthening digital literacy to strengthen the legitimacy of food policies in the digital public sphere. The contribution of this research lies in enriching the global literature on food policy communication in the digital era, particularly in the context of developing countries with complex online participation dynamics.

Keywords Digital food communication; digital literacy; MBG program; social media; social network analysis

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1. INTRODUCTION

Digital transformation has accelerated the dissemination of information about food policy through social media, making public awareness of issues such as the Free Nutritious Meal (MBG) program more immediate and widespread (Latif et al., 2024). In Indonesia, this information flows via digital platforms, not only informing the public but also actively shaping policy legitimacy, as public opinion is rapidly mobilized and expressed through direct interaction with policymakers. Real-time feedback mechanisms on social media offer the public opportunities to voice support and criticism of food policy (Latif et al., 2024). This was evident in the discussion on MBG, which triggered a wide range of responses, ranging from appreciation to sharp criticism, which showed how quickly public opinion can form and evolve in the digital space. The speed at which opinions form demands a deep understanding of how policy narratives are consumed and distributed. Without such an understanding, public programs risk fragile legitimacy when mediated through often polarized, emotionally charged online debates. Therefore, analyzing digital communication patterns in food policy is crucial to ensuring the successful implementation of programs at the grassroots level.

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The study of public opinion in the digital age now relies heavily on computational techniques to capture the essence of large-scale conversations. The use of *machine learning* (ML) algorithms, such as *Support Vector Machines* and *Decision Trees*, has been shown to be effective in classifying sentiment in customer and public interactions on social media (Ahmed et al., 2022; Rahman et al., 2024). The sophistication of this method is further enhanced by incorporating text network features, which improve sentiment classification performance to an AUC of 83% in certain applications (Alnasrawi et al., 2024). This suggests that sentiment analysis accuracy can be significantly improved through the integration of network-based techniques. In addition to sentiment analysis, social network analysis plays an important role in identifying interaction patterns and key actors in online conversations (Zhang, 2025). Network mapping allows researchers to understand how sentiment spreads and influences audience perceptions systemically. By examining the topology of interactions, influential nodes that drive the main information flow can be precisely identified. Identification of these actors is critical to understanding their role in strengthening or weakening the legitimacy of policy messages. Through this approach, research can contribute to understanding symbolic power structures in digital networks, which often determine the success of a food policy narrative in the public sphere.

Although ML methods and network analysis have been widely used, there are urgent empirical gaps that need to be addressed. Previous research has tended to examine sentiment or networks in isolation, often failing to capture the full complexity of public conversation dynamics. Machine learning *models*, for example, still rely heavily on the quality of the training data and may introduce bias in sentiment interpretation. On the other hand, network analysis has limitations in capturing the dynamics of meaning beyond the relational structure. Therefore, integrating ML methods, social network analysis, and qualitative approaches is critical to closing the gap. Qualitative analysis complements quantitative findings by providing context for shifts in sentiment and perception dynamics (Ahmed et al., 2022). By connecting numerical and descriptive data, the study captured nuances that algorithms alone could not detect. The qualitative approach provides a deeper understanding of public perceptions of MBG, including influential psychological and social factors. This is crucial for interpreting the shifting meanings behind the numbers and network patterns. This integration ensures that research results better reflect the complexity of human interaction on social media and reduces the risk of information distortion. This research is urgent because it provides the empirical evidence needed to understand the dynamics of online discourse that are increasingly influenced by algorithms.

The use of integrated research methods ensures that research results better reflect the complexity of human interaction on social media and reduces the risk of information distortion. This research is urgent because it provides the empirical evidence needed to understand the dynamics of online discourse that are increasingly influenced by algorithms. In the context of public policy, polarized discourse can erode public legitimacy and trust in government programs. Therefore, the empirical findings from this analysis are expected to provide policymakers with important guidance for formulating more adaptive communication strategies. Based on this background and urgency, this study aims to answer the following research questions: How is the narrative of the MBG food communication program represented through public sentiment on social media X? What is the role of digital literacy in mitigating negative sentiment to maintain the stability of the MBG policy narrative? Overall, the integration between machine learning-based sentiment analysis, social network mapping, and qualitative approaches in this study provides a comprehensive framework for understanding the complexities of human interaction on social media. This research is urgent because it provides the empirical evidence needed to navigate the dynamics of online discourse that are increasingly influenced by algorithms and polarization. By identifying how negative narratives are formed and the role of key actors in the flow of information, this study's findings are expected to provide policymakers with strategic guidance to formulate more adaptive, credible, and transparent communication strategies. In the end, this effort is not just a technical need for communication, but a democratic imperative to strengthen the legitimacy of government programs amid the challenges of the disinformation era.

2. METHODS

This study employs *a convergent parallel mixed-methods* design that integrates quantitative and qualitative analyses to provide a comprehensive understanding of the phenomenon under study. This approach was chosen because of its ability to deepen insights through a combination of data collection and analysis techniques, conducted independently before combining the findings to reach holistic conclusions (Sciberras et al., 2023; Gamage, 2025). This design aims to facilitate data triangulation to understand how digital discourse and literacy shape public perception of the Free Nutritious Meal (MBG) program. Although this design faces challenges in aligning qualitative and quantitative findings, it is highly effective at capturing the complexity of human interaction in the digital space. The research was conducted in the digital realm, focusing on the social media platform X (formerly Twitter). Data were collected using the Emprit Academic Drone analysis platform from April 1, 2025, to August 31, 2025. This period was chosen to capture the dynamics of discourse when the MBG program became a hot topic in the online public space. The Emprit Academic Drone instrument is used for its ability to capture large-scale data and detect bot accounts through interaction metadata. The subjects of the quantitative analysis consisted of 87,589 public posts that met strict inclusion criteria: (a) contained the keywords "Free Nutritious Meals", "MBG", or "Free Lunch"; (b) issued during the study period; (c) originated from a public account; and (d) was not identified as a bot account. The raw data obtained through *web scraping techniques* is then cleaned of duplicates, spam, and irrelevant content to maintain the validity of the analysis. A sample of 87,589 Twitter mentions (April–Aug 2025) was manually labeled (n = 1,200).

The analysis is carried out through the main stages that complement each other. The first stage is a machine learning-based sentiment analysis that starts with text preprocessing, including tokenization, *stopword removal*, *stemming*, and normalization. The classification model was trained using *the Support Vector Machine* (SVM) and *Decision Tree* algorithms, with an 80/20 split for training and testing. To ensure the reliability of manual labeling prior to automation, the evaluation used the Kappa coefficient, yielding a value of 0.81. This value shows a very strong *level of inter-rater reliability*, so the training data is considered valid and consistent. Meanwhile, the model's technical performance is comprehensively measured through precision metrics, *recalls,* and F1 Scores. The model in this study achieved an F1 score of 0.83, indicating an optimal balance in classifying positive, negative, and neutral sentiments amid the complexity of social media data. The second stage uses Social *Network Analysis* (SNA) to map the key actors and communities in the conversation. The network is built on the definition of *an edge* that includes interactions *between mentions*, *retweets*, and *replies* between users. Technical measurements are carried out by calculating *centrality* to identify the authority of actors and *modularity* to examine the structure of the sub-communities formed.

As a complement to the quantitative data, a purposive, proportionally selected subsample was analyzed thematically. The coding procedure follows a systematic protocol to identify dominant themes, narrative *framing*, and psychological and social factors that affect public perception of the MBG program. The final stage of the research is to triangulate by integrating the results of ML, SNA, and qualitative thematic analysis. This integration ensures that research findings can capture nuances of meaning that often escape detection by algorithms alone. This research upholds digital research ethics by ensuring compliance with platform X's privacy policy and data protection standards. All data analyzed is public and processed anonymously, without involving the user's personally identifiable information (*Personally Identifiable Information*). The use of Emprit Academic Drones as the primary instrument ensures that the data retrieval procedure is carried out in accordance with applicable technical and legal protocols to maintain integrity and transparency throughout the research process.

3. FINDINGS AND DISCUSSION

3.1 Findings

The research data come from a collection of public conversations on Twitter (X) about the Free Nutritious Meals (MBG) program from April 1 to August 31, 2025.

3.1.1 Sentiment in MBG Discourse

Sentiment analysis shows that conversations about MBG are predominantly negative. The distribution details are shown in Table 1.

Table 1. Composition of MBG program sentiment on Twitter

Sentiment	Number of mentions	Percentage (%)
Negative	48,787	55.7
Positive	37,688	43.0
Neutral	1,114	1.3

A total of 87,589 mentions were identified. Of these, the conversations involved 26,409 active author accounts, with 16,361 accounts identified through metadata by the Drone Emprit analysis system.

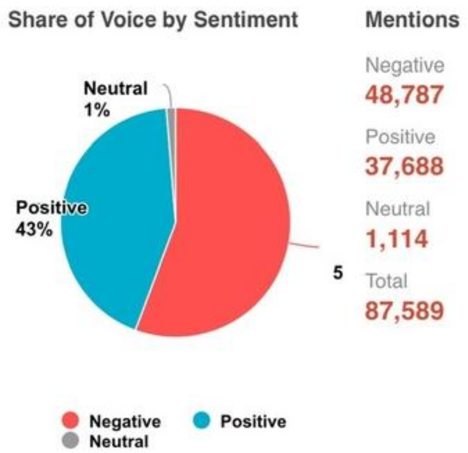

***Figure 1**. Share of voice sentiment MBG (pie chart).*

The graph shows the distribution of sentiment based on the number of recorded conversations. Of the total 87,589 mentions, the majority were negative, at 48,787, or approximately 56%. Positive sentiment accounted for 37,688 mentions, or 43%, while neutral sentiment accounted for only 1,114 mentions, or 1%. This data shows that negative voices still outnumber positive and neutral sentiments.

3.1.2 Daily tren of MBG mention

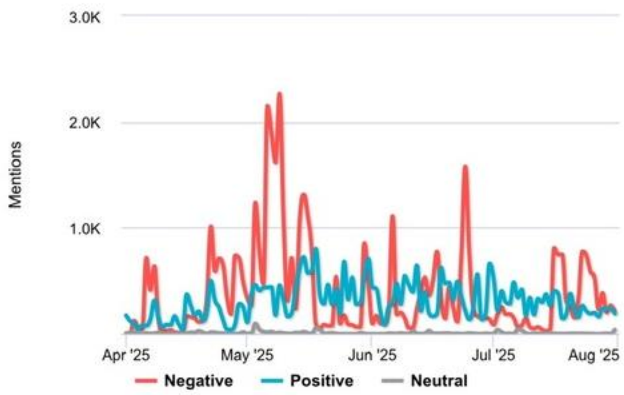

Figure 2. *Daily trend of mentions per sentiment category (time-series, Apr–Aug 2025).*

The temporal visualization (Figure 2) shows the fluctuation in daily conversation volume throughout the study period. The peak was recorded in May 2025, marked by a spike in mentions, particularly in negative categories. Meanwhile, positive sentiment remained relatively stable but remained below the volume of negative conversations.

3.1.3 User interaction on MBG discourse

The interaction data shows engagement patterns that parallel temporal trends. Interaction intensity increased sharply during the peak conversation period in May 2025. Figure 3 displays a graph of interaction trends (likes, retweets, and replies) based on Drone Emprit output.

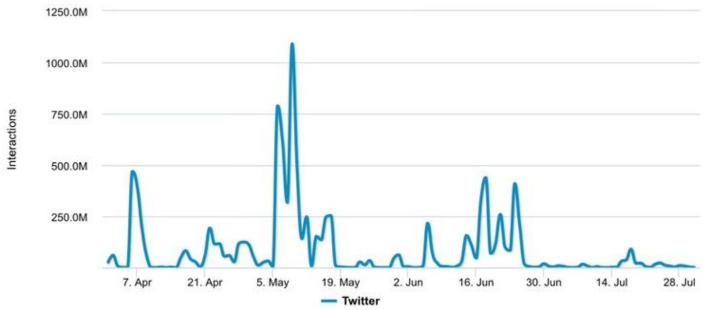

Figure 3*. Trends in user interactions related to MBG (Apr–Aug 2025).*

3.1.4 MBG Program Network Analysis

Social network analysis produces a map of the connections between accounts. A summary of the network metrics is presented in Table 2.

Table 2. MBG Program Network Analysis

Indicator	**Mark**
Number of nodes (accounts)	26,409
Number of edges (mention/retweet/reply)	87,589
Average degree	6.6
Modularity	0.41
Number of communities	7

Network analysis revealed 26,409 accounts involved in the conversation. Interactions between accounts, including mentions, retweets, and replies, created 87,589 edges. An average degree of 6.6 indicates each account interacts with approximately six other accounts. A modularity value of 0.41 yielded seven fairly fragmented yet interconnected communities.

3.1.5 Influencer based on impression

Drone Emprit identified several accounts with deep impression and mention reach. To protect privacy, account identities are not displayed. A summary of the top 5 accounts by impressions is presented in Table 3, coded anonymously.

Table 3. Influencers based on impressions

Account Code	Impressions (relative)	Mentions (relative)	Position in the network
Influencer 1	Very high	High	Main hub
Influencer 2	High	High	Cluster 1
Influencer 3	Medium	High	Cluster 2
Influencer 4	Medium	Medium	Cluster 3
Influencer 5	Medium	Low	Peripheral

Influencer 1 has very high impressions and a high number of mentions, making it the main hub in the network. Influencer 2 occupies Cluster 1 with high impressions and high mentions, indicating a significant role in the conversation within their community. Influencer 3 is in Cluster 2 with moderate impressions but high mentions, indicating active engagement despite limited reach. Influencer 4 is in Cluster 3, with moderate impressions and mentions, and thus acts as a moderate hub. Influencer 5 is in a peripheral position with moderate impressions but low mentions, indicating limited involvement in the conversation network.

3.1.6 Demographic analysis of actors

Demographic analysis (based on identified accounts) indicates a predominance of male users. Details are shown in Table 4.

Table 4. Demographic analysis of actors

User Type	Authors	Authors (%)	Posts	Posts (%)
Non-organizational	14,862	90.8	34,062	89.6
Organization	1,499	9.2	3,955	10.4

A demographic analysis of actors shows that the majority of conversations are dominated by non-organizational accounts, namely 14,862 authors or 90.8% with 34,062 posts, equivalent to 89.6%. meanwhile, organizational accounts only numbered 1,499 or 9.2%, contributing 3,955 posts or 10.4%.

Table 5. Demographic Analysis Based On Gender

Gender	Authors	Percentage (%)	Posts	Percentage (%)
Man	11,400	69.5	25,800	67.9
Woman	5,000	30.5	12,200	32.1

By gender, men dominated with 11,400 authors (69.5%) and produced 25,800 posts (67.9%). Women accounted for 5,000 authors (30.5%) and 12,200 posts (32.1%). This data shows that conversations are driven more by non-organizational individuals and men. From a total of 87,589 mentions, a stratified subsample was selected for thematic content analysis. The subsample was selected based on sentiment category (positive, negative, or neutral) and the network's community distribution. A total of 1,200 posts were recorded as qualitative analysis units.

3.2 Discussion

3.2.1 The Dynamics Of Negativity Bias And Policy Legitimacy

The dominance of negative sentiment, which reached 55.7% or 48,787 mentions in the Free Nutritious Meal (MBG) discourse, provides empirical confirmation of the validity of *the theory of negative bias* in the digital public space. This phenomenon shows that information that is critical, skeptical, or psychologically threatening tends to elicit much more intense engagement than positive narratives. The speed and reach of social media enable false narratives to spread more rapidly than corrections or evidence-based explanations (Hassani et al., 2024). In the context of MBG's policy, public criticism is amplified more quickly because it touches on sensitive issues related to social psychology (Rozin & Royzman, 2001; Soroka & McAdams, 2015), especially related to the level of public trust in the integrity and transparency of the government in managing the state budget.

The data shows that these spikes in negative sentiment often drown out constructive technical explanations, creating biased collective perceptions on social media. This confirms that policy legitimacy in the digital space is very fragile. When public discourse is dominated by negative narratives, credible messages about the health benefits and improvements in national nutrition tend to be difficult to reach a wider audience because they are drowned out by the speed of the diffusion of emotionally charged information. The tone of online discussions tends to grow increasingly negative, particularly within polarized communities (Zollo et al., 2015). The tendency to prioritize and react more strongly to adverse information means that negative aspects of food policies, such as the health risks associated with processed foods, receive disproportionate attention (Gommeh, 2022).

Furthermore, the qualitative findings reinforce indications that public concern about bureaucratic efficiency and the potential politicization of policies are the main catalysts for the strengthening of this negative sentiment. This aligns with the argument that without strong network intervention strategies, such as the involvement of verified key actors (*influencers*) and *real-time monitoring*, negative narratives will continue to dominate and erode public trust. Therefore, strengthening public digital literacy is urgent so that the public can distinguish critically between substantive policy criticism and destructive negative amplification, thereby maintaining the sustainability of government program legitimacy in the digital public space. The dominance of negative sentiment at 55.7% in MBG's discourse reveals the vulnerability of policy legitimacy, triggered by the government's communication structure failing to compensate for the speed of information asymmetry in the digital space. This phenomenon proves that the mechanism *of negative bias* systematically drowns out the narrative of health benefits by amplifying the issues of politicization and budget efficiency, which attract more emotional public attention.

3.2.2. Event-Driven Agenda Setting

The significant surge in conversation volume that occurred in May 2025 is a tangible manifestation of the event-driven agenda-setting mechanism in the digital space. In this phenomenon, the momentum of a technical announcement or a particular policy event forces the public to respond collectively and simultaneously. In contrast to the traditional media cycle, which tends to follow an orderly, sustainable narrative, the digital discourse regarding the Free Nutritious Meal (MBG) program is 'bursty'. Active engagement on Twitter often exhibits a bursty structure, with discussions occurring in concentrated intervals rather than a steady stream (Sanli & Lambiotte, 2015). This explosion reflects how attention and participation fluctuate according to situational relevance and social momentum. This characteristic is characterized by the appearance of very intense opinions in a short duration, but they fade quickly after the initial stimulus loses its appeal.

This communication pattern relies heavily on external stimuli, such as provocative statements from key figures, viral uploads from *influencers*, or the release of official budget data. This confirms that public attention in cyberspace is highly selective and governed by the principle of the *attention economy*. In an ecosystem full of information noise, only issues with a high emotional charge or dramatic urgency make it through the audience's attention filter. This phenomenon has implications for the fragility of the stability of policy issues on social media. While a food policy issue like MBG can be on the national agenda in a matter of hours, the absence of a well-managed, sustainable narrative can keep public understanding on the surface. Therefore, the surge in data in May 2025 proves that the government not only needs to be present when events occur but also must manage information sustainability so that the policy agenda does not become a momentary trend easily distorted by negative narratives. Understanding this *event-driven* pattern is crucial for public communicators to determine the most appropriate time to respond to fluctuating public opinion dynamics.

The bursty *surge* in conversation volume in May 2025 indicates that public attention to the MBG program relies heavily on dramatic external stimuli but fails to foster a deep, sustained policy understanding. This *event-driven agenda-setting pattern shows* the vulnerability of government food communication, which is only reactive, leaving the discourse space easily dominated by emotional *information noise*. The inability to sustain a stable narrative beyond viral momentum risks reducing the substance of national nutrition policy to a momentary trend, prone to distortion by digital actors with partisan interests.

3.2.3 The Role of Central Actors and Representation Bias

An analysis of the communication network's structure reveals that the narrative of the Free Nutritious Meal (MBG) program does not develop organically from the *grassroots* but is strongly influenced by the concentration of impressions on a small number of central actors. This phenomenon is evident in the dominance of interactions centered on certain figures (Influencers 1 and 2), who serve as *opinion leaders,* directing the flow of information and shaping public perception of these policies. Digital influencers are increasingly shaping public opinion on food policy and related health initiatives. Through storytelling, personal experiences, and recommendations, they cultivate parasocial relationships that heighten audience trust and engagement (Pereira, 2023). Citrawijaya and Jannah (2025)emphasize how influencers strategically use visual and rhetorical techniques to enhance engagement, making their content more relatable and memorable. This communicative strategy aligns with findings by McBeth et al. (2012), who showed that interest groups employ extreme visualizations to capture attention and evoke strong reactions. While such methods can increase awareness, they also risk oversimplifying complex policy issues, potentially leading to a biased or incomplete public understanding. The reliance on these key actors suggests an information asymmetry in which the grand narrative is determined more by digital authority holders than by the collective discussion of the wider community.

Centrality of degrees explains the role of hubs in disseminating information, while centrality between highlights the role of bridges between communities, despite their limited numbers (Brugnoli et al., 2019). Qualitative analysis shows that in echo space, confirmation bias and information selectivity reinforce internal narratives (Turetsky & Riddle, 2018). This condition makes it increasingly difficult to bridge different perspectives as similar narratives continue to be amplified. Thus, the fragmentation of the network in the case of MBG suggests the formation of an echo chamber that limits the space for cross-perspective dialogue. Polarization further intensifies the impact of misinformation by shaping how users interact with one another. Online discussions are often structured by homophily, meaning individuals prefer to engage with like-minded peers, thereby reinforcing pre-existing beliefs (Jiang, 2022). This selective interaction deepens divisions and hardens positions in public debate. As polarization increases, opportunities for cross-sectoral dialogue diminish, making policy communication vulnerable to distortion. The result is a communicative environment in which achieving consensus is increasingly difficult.

The role of algorithms in amplifying echo chambers exacerbates this problem, as digital platforms prioritize content that aligns with user preferences. This personalization creates a feedback loop that exposes individuals primarily to information that confirms their worldview (Wahab, 2024). Such algorithmic curation limits exposure to diverse perspectives, thus narrowing the discursive space for balanced debate. For food policy, this means that supportive and critical narratives rarely intersect in meaningful ways. On the contrary, fragmentation reinforces perceptions of division and undermines collective deliberation over public programs. The inequality in representation is increasingly evident in user demographic data, where male users dominate at 69.5%, while women reach only 30.5%. In addition, engagement was dominated by individual or non-organizational accounts at 90.8%. These statistics reflect a real gender bias in participation in digital political communication in Indonesia. This aligns with the literature on the masculinity of digital public spaces, which notes that women's voices are often marginalized in public policy debates perceived as macroeconomic, technical, or political. Male homophily in academic practice also demonstrates how male voices are more dominant in scientific publications (Smyth, 2023). The digital space, which is supposed to be an arena for inclusive deliberation, instead replicates the conventional patriarchal structure, in which strategic policy issues are more often occupied by male perspectives. In the context of MBGs, the dominance of male users and non-organizational groups makes certain narratives more prominent. This results in the voices of women and organizations being less heard in online conversations. Thus, representational bias in MBGs should be considered as a significant factor in interpreting research findings.

The impact of this representation bias is very significant on the depth of food policy discussions. Women, who traditionally and practically often play the leading role in food regulation and family food management, are underrepresented in the MBG discourse. As a result, crucial domestic perspectives, such as the practical aspects of food distribution, daily nutritional quality, and the direct impact on child well-being, have become minimal in mainstream conversation. This lack of representation of women's voices causes food policy discourse to lose its valuable empirical dimension from the perspective of household nutrition managers. Without gender inclusivity, the legitimacy and effectiveness of food policies in the digital public space are threatened, as they risk becoming uneven, ignoring the voices of the most affected groups, and failing to account for the realities of policy implementation at the family level. Therefore, strengthening the participation of women and marginalized groups in digital discourse is an absolute requirement to create more responsive and equitable policies.

3.2.4 Strategic Implications: Digital Literacy and Verified Interaction

The results of this study as a whole confirm that the government's communication strategy for disseminating food policies, especially the Free Nutritious Meal (MBG) program, cannot be conducted conventionally or in a one-way manner. The dynamics of social media, which are highly fluid and fast-paced, demand a transformation in how countries interact with their citizens in the digital space. One of the most pressing needs is the implementation of *a real-time monitoring* mechanism that can detect a surge in negative sentiment instantly, before the narrative is amplified into a broader legitimacy crisis. Without evidence- and data-driven interventions, government technical explanations will always lag behind the speed of information dissemination driven by algorithms and negative biases. In addition to the technical aspects of monitoring, strengthening digital literacy must be a key pillar of long-term communication strategies. Digital literacy is not just a technical ability to use a platform, but a critical competence for individuals to independently verify the narratives circulating in *echo chambers*. Latif et al (2024) argue that the proliferation of echo chambers constrains individuals' exposure to diverse perspectives, reinforcing preexisting beliefs and biases. A highly literate society will be better able to interrogate misleading information frames and reject the amplification of unfounded negative narratives. Individuals equipped with strong digital literacy skills are better able to critically evaluate the credibility of online information. This capacity is particularly crucial in contexts where misinformation fosters phenomena that directly undermine public trust (Germani et al., 2022; Matagi, 2024).

Digital literacy constitutes a crucial foundation for enabling citizens to critically engage with food policy messages disseminated in the digital sphere. It provides individuals with the analytical skills necessary to interrogate narratives circulating across social media and other online platforms. By fostering critical thinking, digital literacy enhances users' capacity to recognize biases and framing techniques embedded in policy communication (Mann, 2017). This is crucial, given that the study's results show that information fragmentation and polarization are particularly strong in MBG discussions, where users tend to remain in groups that reinforce their own opinions. Finally, interaction with key actors or *opinion leaders* who have functional authority, such as nutritionists, academics, or verified community leaders, becomes a strategic instrument to balance the dominance of negative narratives. The involvement of these actors serves as a bridge of trust between the government and the community. Crafting culturally resonant, evidence-based messages enables communicators to foster greater relatability and acceptance of information (Niederdeppe et al., 2024). By disseminating evidence-based, culturally resonant information from trusted actors, governments can ensure that credible information reaches a wider, more diverse audience. The synergy between data monitoring, literacy education, and collaboration with influential actors is a democratic mandate to create a digital public space that is healthier, more transparent, and able to strengthen the legitimacy of national food policy in the era of disinformation.

These findings emphasize that the success of a policy is not only determined by the quality of the program in the field, but also by the robustness of its communication infrastructure in the cyber world. Critical Analysis: A critical analysis of these findings shows that the dominance of negative sentiment at 55.7% is not simply a reflection of organic dissatisfaction but rather a manifestation of structural failures in the design of government policy communication. Network fragmentation, with a modularity value of 0.41, indicates extreme polarization, in which the digital space shifts its function from the deliberative arena to a set of *echo chambers* that close off opportunities for constructive dialogue. Through the lens of *negativity bias*, it can be seen that the speed of diffusion of negative information that undermines the government's integrity is much more effective at attracting public attention than rigid technical explanations. This confirms the existence of an information power asymmetry where certain central actors are able to dictate the main narrative, while the voices of marginalized groups, especially women, who are only 30.5% represented, continue to be marginalized in strategic debates. Therefore, the fragility of the MBG policy's legitimacy in the digital space demonstrates that the current society's digital literacy is not strong enough to stem the negative amplification driven by the motive of systemic politicization.

4. CONCLUSION

This study concludes that the dynamics of public discourse regarding the Free Nutritious Eating (MBG) policy on platform X during April to August 2025 are dominated by negative sentiment at 55.7%. A significant surge in conversations occurred in May 2025 as a collective response to the budget technical announcement, confirming the existence of *an event-driven agenda-setting* pattern. These findings are based on a solid methodological framework, in which sentiment classification using *Machine Learning algorithms* (SVM and *Decision Tree*) demonstrates reliable technical performance with an F1-score of 0.83. The validity of this data is further reinforced by the high reliability of manual labeling, as demonstrated by Cohen's Kappa of 0.81. Structurally, the communication network formed is fragmentary, with a modularity value of 0.41, indicating the presence of seven main sub-communities that tend to be trapped in *echo chambers*. The author recognizes several limitations in this study that should be noted for future readers and researchers. First, there are challenges related to dataset inconsistencies caused by technical fluctuations in the platform APIs and by complex data noise. Second, although *the Machine Learning* workflow has undergone rigorous metric evaluation, the classification model still struggles to detect sarcasm and to use local Indonesian slang effectively. Third, the qualitative documentation in this study was limited to a subsample of 1,200 uploads. Although proportionately selected, they may not have captured the full depth of the psychological motives of the wider user population.

Based on these empirical findings, this study formulates several specific practical recommendations. Governments are advised to shift from a one-way communication strategy to a rapid-response model that can intervene in negative narratives during *bursty peaks*. Given the dominance of central actors, strategic collaboration with actors who have verified information authority is needed to balance information bias. In addition, communication policies must be more inclusive by targeting women's groups, who, despite being the main stakeholders in family nutrition management, still have minimal participation in MBG's digital discourse (only 30.5%). In the end, integrating real-time sentiment monitoring and strengthening people's digital literacy are the keys to maintaining public legitimacy and trust in national food policy in the digital era. This research positions its novelty on the theoretical integration between food communication and digital literacy to dissect the dynamics of national nutrition policy, a perspective that is still rarely explored in the study of public communication in Indonesia. Methodologically, this study went beyond conventional sentiment analysis by combining *machine learning* algorithms (which have high accuracy in *Social Network Analysis*) to map the spatial structure of information fragmentation. His empirical findings reveal the crucial fact that the dominance *of negative bias* at 55.7% is not just an overflow of emotions but a direct impact of low digital literacy, which leads to the emergence of isolated *echo chambers*. Furthermore, this study makes an original contribution by identifying gender representation gaps, where women's participation in digital food discourse is very low (30.5%), thereby providing the basis for a more inclusive, real-time, response-based policy communication model.

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