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Aspect-Based Sentiment Analysis of Public Opinion on the Free Nutritious Meal Program using BERTopic on X

Carmen Emanuela Dwiva Lisapaly[1], Luther Alexander Latumakulita[2], Rillya Arundaa[3]
[1,2,3]Information Systems, Universitas Sam Ratulangi, Indonesia
[1]carmenlisapaly106@student.unsrat.ac.id, [2]latumakulitala@unsrat.ac.id,
[3]rill@unsrat.ac.id

Abstract: This study aims to analyze public opinion on the Free Nutritious Meal (MBG) Program on the X platform using an Aspect-Based Sentiment Analysis (ABSA) approach with BERTopic-based aspect extraction. Unlike previous studies that primarily perform sentiment classification at the overall text level, this study identifies specific aspects within public discussions to provide more fine-grained insights. Twitter data were collected and preprocessed, followed by topic modeling using BERTopic to extract topics that were subsequently defined as aspects. Topic quality was evaluated using topic coherence (c_v) and topic diversity metrics. The modeling process initially produced 36 topics with a coherence score of 0.4446 and a diversity score of 0.8541. After relevance-based selection, 18 topics were retained as aspects, with the coherence score increasing from 0.4446 to 0.5370 and the diversity score increasing from 0.8541 to 0.8611. Sentiment labeling was then performed using the Twitter-XLM-RoBERTa model to determine the distribution of positive, negative, and neutral sentiments across each aspect. The results demonstrate that the proposed ABSA approach with BERTopic-based aspect extraction provides a more structured and insightful mapping of public opinion, enabling the identification of aspects with the highest levels of support and indications of opposition toward the MBG Program. These findings are expected to serve as a basis for consideration in data-driven policy evaluation and support more informed decision-making.
Keywords: Aspect-Based Sentiment Analysis, BERTopic, Sentiment Analysis, X, Public Opinion, Free Nutritious Meal Program

1. INTRODUCING

The Free Nutritious Meal (MBG) Program is one of the Indonesian government's strategic policies aimed at improving students' nutritional status and supporting human resource development [1]. Since its implementation, the program has generated diverse public responses widely expressed on social media, particularly on the X platform, which serves as an open space for real-time public discourse [2]. These opinions reflect various perspectives, ranging from support for the program's potential benefits to criticism regarding its implementation, including issues related to distribution, budgeting, and governance [3], [4], [5].

Previous studies have shown that sentiment analysis of the MBG Program has been conducted at the overall text level. [6] found that negative sentiment tends to dominate public opinion on the program using IndoBERT. In addition, [7] applied a topic modeling approach to identify discussion topics without linking sentiment analysis at the aspect level.

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These approaches still have limitations, as they do not provide an in-depth understanding of specific aspects that drive public support or opposition.

To address these limitations, this study applies Aspect-Based Sentiment Analysis (ABSA), which enables sentiment analysis at the aspect level [8], [9]. Unlike traditional sentiment analysis at the document level, which only provides a general overview of sentiment toward an entire topic, ABSA allows opinion analysis to be conducted based on specific aspects contained within a topic. This approach demonstrates that ABSA can provide more detailed and fine-grained sentiment analysis for each aspect within a topic compared to conventional sentiment analysis methods that do not explicitly consider aspects [8], [9].

In addition, this study employs BERTopic for aspect extraction, an embedding-based topic modeling method capable of capturing the semantic meaning of text in a contextual manner, thereby producing more coherent and relevant topic groupings aligned with the dataset content [10]. BERTopic is chosen to overcome the limitations of frequency-based topic modeling methods such as Latent Dirichlet Allocation (LDA), which are less effective in capturing semantic context in short text data such as tweets [11]. This makes BERTopic superior to LDA, as it relies not only on word frequency but also on contextual meaning, resulting in more representative topics.

Overall, the combination of ABSA and BERTopic provides advantages over previous approaches, as it not only enables general sentiment analysis but also directly links sentiment to contextually extracted aspects, resulting in a more in-depth, structured, and informative analysis.

Based on this background, this study aims to analyze public opinion on the MBG Program on the X platform using an Aspect-Based Sentiment Analysis (ABSA) approach with BERTopic-based aspect extraction, as well as to evaluate the quality of the generated topics and identify sentiment distribution across each aspect. This research is expected to provide more comprehensive insights into public perception and serve as a data-driven reference for policy evaluation.

The main contribution of this study lies in the integration of BERTopic as an embedding-based aspect extraction method with Aspect-Based Sentiment Analysis (ABSA) within a unified analytical framework. This approach differs from previous studies that generally separate sentiment analysis and topic modeling into distinct processes. Therefore, this study provides a more specific and structured mapping of public opinion compared to conventional approaches.

2. RESEARCH METHODOLOGY

This study employs a quantitative approach based on text data analysis to examine public opinion on the Free Nutritious Meal (MBG) Program on the X platform. The approach consists of several stages, including data collection, preprocessing, topic modeling using BERTopic, and aspect-level sentiment analysis.

2.1 Research Stages

This study consists of seven main stages arranged systematically and interrelated, starting from data collection to final analysis. The first stage is data collection, which involves gathering tweets related to the MBG Program from the X platform based on predefined keywords and a specified time period. The second stage is data preprocessing, which includes text cleaning and preparation to ensure that the data is suitable for analysis. The third stage is topic modeling using BERTopic, which involves embedding generation, dimensionality reduction, clustering, and topic representation. The fourth stage is topic evaluation, which applies topic coherence (c_v) and topic diversity metrics to assess the quality of the generated topics. The fifth stage is topic selection and aspect naming, in which relevant topics are selected and aspects are labeled in a semi-automatic manner

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using a Large Language Model (LLM), followed by manual verification. The sixth stage is sentiment classification, which utilizes an XLM-RoBERTa-based model to categorize tweets into positive, neutral, and negative classes. The seventh stage is sentiment aggregation, which calculates the sentiment distribution for each aspect to identify public opinion tendencies toward the MBG Program. The complete research workflow is illustrated in Figure 1.

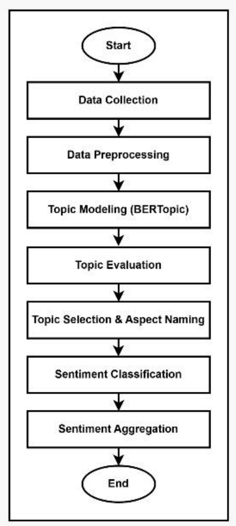

Figure 1. Research Stages

2.2 Data Collection

The data used in this study consist of public tweets collected from the X platform, focusing on discussions related to the MBG Program. Data collection was conducted from April 1, 2025 to October 31, 2025 to capture public responses during the program's implementation phase. The dataset focuses on Indonesian-language tweets, including mixed-language tweets with a dominant use of Indonesian, while non-Indonesian tweets were excluded from the analysis.

Data were collected using several keywords related to the MBG Program, including "Program Makan Bergizi Gratis", "Makan Bergizi Gratis", "Program Makan Siang Gratis", "Makan Siang Gratis", and "MBG", along with other variations referring to the program. These keywords were used to capture a wide range of public discussions on the X platform.

The data collection process was conducted incrementally on a monthly basis to ensure the stability of the crawling process, with a target of approximately 2,500 tweets per month. The collected data were stored in Comma-Separated Values (CSV) format and subsequently merged into a single dataset for further analysis. A summary of the tweet distribution for each month is presented in Table 1.

Table 1. Distribution of Tweet Data per Month

Month	Number of Tweets
April	815
May	2.501
June	2.517
July	2.506
August	2.517
September	2.505
October	2.509
Total	**15.870**

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2.3 Data Preprocessing

The preprocessing stage was carried out to clean and prepare the text data before performing topic modeling and sentiment analysis. This process aims to reduce noise, standardize text representation, and ensure that the data used are relevant to discussions of the MBG Program. The preprocessing steps in this study consist of the following main processes.

a) Text Cleaning

At this stage, text cleaning was performed by converting all characters to lowercase and removing elements that do not represent the main content of the tweets, such as URLs, mentions (@username), retweet headers (RT), and emojis. In addition, punctuation marks and standalone numbers were removed to reduce noise in the text data [2].

b) Text Normalization

The normalization stage was conducted to standardize word forms so that they can be processed consistently by the model. This process includes hashtag normalization related to the MBG Program, handling repeated characters, converting informal words into their standard forms, and merging important phrases into single tokens using pattern-based rules (regular expressions). This step aims to preserve semantic meaning while reducing unnecessary variations in word forms [12].

c) Filtering

The filtering stage was conducted to ensure that the data used are relevant and of high quality. This process includes removing tweets that are not related to the MBG Program, eliminating duplicate data, filtering language to retain Indonesian-language tweets, and applying rule-based filtering to remove tweets with insufficient information content. This step ensures that the analyzed data accurately represent discussions relevant to the MBG Program [13], [14].

d) Stopword Removal

At this stage, common words (stopwords) that do not carry significant meaning in text analysis were removed to improve the focus on words that represent the main content of discussions related to the MBG Program [2].

2.4 BERTopic Modeling

In this stage, topic modeling was performed using the BERTopic method to identify discussion topics within the tweet data. This method integrates embedding, dimensionality reduction, clustering, and term weighting techniques to generate meaningful topic representations [10]. The entire modeling process was conducted using GPU acceleration to improve computational efficiency.

a) Embedding

At this stage, all preprocessed text data were transformed into numerical representations using the IndoBERTweet model (indolem/indobertweet-base-uncased), which has been trained on Indonesian Twitter data. This process aims to capture semantic meaning in vector form, enabling the measurement of similarity between tweets. The output of this stage is an embedding matrix, which is then used as input for the dimensionality reduction stage.

b) Dimensionality Reduction

This stage was performed to reduce the dimensionality of the embedding vectors using the Uniform Manifold Approximation and Projection (UMAP) algorithm. Dimensionality

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reduction aims to simplify data representation while preserving the underlying structure of the data, thereby facilitating the clustering process [15]. The parameters used in this stage are presented in Table 2.

Table 2. UMAP Parameters in BERTopic

Parameter	Value
n_neighbors	15
n_components	5
min_dist	0.0
metric	cosine

The output of this process is a lower-dimensional representation of the data, which is used as input for the clustering stage.

c) Clustering

The clustering stage was performed using the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm to group tweets based on semantic similarity. This method is capable of identifying high-density clusters and distinguishing data points that are considered noise (outliers) [16]. The parameters used in this stage are presented in Table 3.

Table 3. *Clustering* Paramaters (HDBSCAN)

Parameter	Value
min_cluster_size	15
metric	Euclidean
cluster_selection_method	eom

The output of this stage consists of clusters representing initial topics, along with a number of data points identified as outliers.

d) Tokenization

At this stage, tokenization and word frequency matrix construction were performed using CountVectorizer. This process aims to split text into word units and build a frequency-based representation of words within each cluster. The parameters used are presented in Table 4. The use of unigram and bigram features allows the model to capture both individual words and meaningful phrases within the context of the discussion.

Table 4. Tokenization Parameters (CountVectorizer)

Parameter	Value
ngram_range	1,2
min_df	2
max_df	0.85

e) Topic Representation

Topic representation was obtained through a weighting process using the Class-based Term Frequency–Inverse Document Frequency (c-TF-IDF) method, which is part of the BERTopic framework [10]. This method assigns weights to words based on their importance within a cluster compared to other clusters. As a result, the most representative words in each topic can be identified as top terms.

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f) Topic Reduction

In this stage, similar topics were merged based on their word weight distributions (c-TF-IDF). This process aims to reduce the number of topics. After the reduction process, topic representations were updated, and the highest-weighted words were used to represent each topic.

2.5 Topic Evaluation

Topic evaluation was conducted to assess the quality of the topics generated by the BERTopic model. This evaluation aims to measure the degree of semantic relatedness among words within a topic, as well as the diversity of keywords across topics. In this study, two main evaluation metrics were used, namely topic coherence (c_v) and topic diversity.

a) Topic Coherence (c_v)

Topic coherence is a metric used to measure the degree of relatedness among words within a topic. It evaluates how frequently words in a topic co-occur within the same context, thereby reflecting the clarity of the underlying semantic meaning. Coherence values range from 0 to 1, where higher values indicate stronger word associations. In this study, the c_v coherence metric was employed due to its strong correlation with human judgment in evaluating topic quality [17]. The computation of this metric was performed using the Gensim library, which integrates several components such as sliding window, Normalized Pointwise Mutual Information (NPMI), and cosine similarity to calculate word association scores within topics. There is no fixed threshold for coherence values, as they depend on dataset characteristics and model parameters. In short-text data such as tweets, coherence values tend to be lower due to limited text length and lower word co-occurrence frequency [18].

b) Topic Diversity

Topic diversity is a metric used to measure the degree of keyword variation across topics. It evaluates how distinct the words in each topic are compared to one another. Diversity values range from 0 to 1, where higher values indicate that topics contain more varied keywords and exhibit less overlap [19]. This metric complements coherence evaluation by ensuring that the generated topics are not only internally coherent but also clearly distinguishable from one another.

2.6 Topic Selection and Aspect Naming

After the topic evaluation process, the next step is to select topics that are relevant to the MBG Program. This process aims to ensure that the topics used in subsequent analysis accurately represent issues related to the program. Topic selection was performed manually based on the interpretation of top terms for each topic, by assessing whether the words form a coherent and relevant discussion.

a) Topic Selection

In this study, topic coherence was not used as the primary criterion for topic selection. This is due to the characteristics of short-text data such as tweets, where word co-occurrence tends to be low, potentially resulting in relatively low coherence scores even when the topics are meaningful. Therefore, the selection process focused on the semantic interpretation of top terms and the contextual content of tweets within each cluster.

b) Aspect Naming

After identifying relevant topics, the next step is to assign aspect labels to each topic. After identifying relevant topics, the next step is to assign aspect labels to each topic. This

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process aims to provide a clearer representation of the issues discussed in each topic, enabling aspect-level sentiment analysis (Aspect-Based Sentiment Analysis).

Aspect naming was conducted in a semi-automated manner using a Large Language Model (LLM), namely ChatGPT, to generate concise aspect labels based on the top terms of each topic. The generated labels were then manually verified to ensure alignment between the aspect names and the topic context. Adjustments were made when necessary to obtain the most representative aspect labels.

2.7 Sentiment Analysis

After the final dataset was prepared, the next step was to perform sentiment labeling on each tweet. Sentiment analysis was conducted using the cardiffnlp/twitter-xlm-roberta-base-sentiment model, a transformer-based model built on XLM-RoBERTa that has been trained for sentiment classification tasks on Twitter data [20].

The labeling process was applied to tweet texts to classify opinions into three sentiment categories: positive, neutral, and negative. The model outputs probability scores for each category, and the final label is determined based on the highest probability. Although the model has been trained on Twitter data, variations in language usage, such as informal expressions, may affect prediction results. Therefore, after the automated labeling process, the classification results were manually reviewed to ensure consistency between sentiment labels and the context of the tweets.

2.8 Sentiment Aggregation

After sentiment labeling was completed, sentiment aggregation was performed for each aspect to analyze the distribution of public opinion regarding the MBG Program. Aggregation was conducted by calculating the number and percentage of positive, neutral, and negative sentiments for each predefined aspect. This stage aims to identify patterns of public opinion across different aspects. The aggregated results are then used as the basis for analysis and interpretation in the Results and Discussion section.

3. RESULT AND DISCUSSIONS

This section presents the research findings obtained based on the methodological stages described previously, including topic modeling, topic selection, aspect identification, and sentiment distribution analysis. In addition, this section provides an interpretation of the results and relates them to previous studies and the implementation context of the MBG Program.

3.1 Topic Modeling Results

Topic modeling in this study was conducted using the BERTopic method to identify discussion topics in tweets related to the MBG Program. Based on the modeling results, 36 topics were obtained after a topic reduction process from the initial 47 clusters. This reduction was performed by merging similar topics to produce more concise and interpretable topic representations.

The quality of the generated topics was evaluated using topic coherence (c_v) and topic diversity. The evaluation results show a coherence score of 0.4446, indicating that the level of word association within topics is acceptable, particularly for short-text data such as tweets. Meanwhile, the topic diversity score of 0.8541 indicates a high level of keyword variation across topics, suggesting that the topics are generally distinct and non-overlapping. The relatively low coherence value is consistent with the characteristics of Twitter data, which are limited in length, resulting in lower word co-occurrence frequency. At the same time, the high diversity score indicates that the model is capable of generating semantically distinct topics.

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Overall, these results demonstrate that the BERTopic model is able to generate a sufficiently structured set of initial topics as a foundation for further analysis. A summary of the topic evaluation results is presented in Table 5.

Table 5. Topic Evaluation Results

Topic Reduced	Top Terms	Coherence (c_v)
0	makanbergizigratis, program, keracunan, lanjutkan, anak, indonesia, gizi, rakyat	0,4022
1	aparatkeamanan, unitpelaksana, jaga, langkah, kualitasmakanan, semangat, bangga, program	0,7869
2	makan, menu, basi, makanbergizigratis, anak, lauk, makanan, enak	0,4844
3	unitpelaksana, aktordaerah, aktorlokal, menu, ulat, dapur, temuan, siswa	0,3992
4	makanbergizigratis, maaf, menolak, hubungan, pres, memaksakan, beresin, ego	0,4153
5	kasuskeracunan, dianiaya, wartawan, pasar, terulang, diduga, meliput, liput	0,5972
6	abis, makanbergizigratis, sempet, dah, emg, ditemenin, nyungsep, jir	0,2980
7	program, presiden, makanbergizigratis, pemerintah, perekonomian, pengamat, inspiratif, mitra	0,2860
8	susu, liter, telur, kotak, dimakan, cm, nasi, makan	0,3055
9	dapur, pimpinan, daerah3t, dibangun, umkm, makanbergizigratis, bangkit, hukum	0,2700
10	makanbergizigratis, kak, berpisah, ikonik, 3cm, asyem, mg, utility	0,3304
11	gratis, beracun, makan, makanan, kuliah, sekolah, pendidikan, singkatan	0,4536
12	proyek, korupsi, rakyat, ladang, penguasa, makanbergizigratis, pemerentah, berjamaah	0,3517
13	kerja, lapangan, job, lowongan, luas, peluang, melimpah, terbuka	0,3189
14	lo, si, kasian, tbtb, pinter, buzzernya, monyet, anjing	0,3421
15	presiden, korban, dana, deh, tuntas, makanbergizigratis, asbun, nyari	0,2852
16	papua, tokoh, adat, program, anakanak, tanahpapua, mendukung, cerdas	0,5643
17	beracun, haters, berhasil, hidangan, makanbergizigratis, nder, bergizi, terimakasih	0,2975
18	anaksekolah, anakanak, sekolah, anak, stunting, uda, menyasar, ngasih	0,3548
19	indonesia, emas, maju, sejahtera, wujudkan, investasi, langkah, fonsasi	0,5118
20	harga, ayam, stok, telur, pakan, singkong, permintaan, ngeluh	0,4634
21	merah, putih, koperasi, kopdes, pelototin, suplier, komplit, rakyat	0,6283
22	ekonomi, masyarakat, program, dampak, bukti, pemerintah, dunia, populasi	0,4181

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Topic Reduced	Top Terms	Coherence (c_v)
23	terimakasih, hewan, laut, makan, bergula, justin, masmas, ginger	0,3370
24	babi, minyak, mengandung, tray, nampan, food, halal, impor	0,9583
25	koordinasi, tim, rapat, rutin, bentuk, sense, solid, disiplin	0,6559
26	sibuk, ngurusin, capek, urusin, ngurus, bahas, isu, pengalihan	0,1868
27	shift, masak, katering, standar, kebanyakan, sesuai, gtu, lelaki	0,2834
28	aktorlokal, wakil, kepala, pemukulan, sidak, petugas, unitpelaksana, polisi	0,7459
29	berita, gampang, orang, merugikan, asumsi, diomongkan, lanjutkan, percaya	0,3420
30	selesai, email, pengawasan, comment, mencapai, share, tonton, like	0,3940
31	kapal, ditilep, 1t, pdhl, beli, perhari, anggaran, programprogram	0,2446
32	sekolahswasta, sekolah, boarding, nolak, school, kak, setuju, segini	0,4641
32	sekolahswasta, sekolah, boarding, nolak, school, kak, setuju, segini	0,4641
33	nasi, ayam, tumis, menu, jeruk, kacang, goreng, disajikan	0,9635
34	berenang, berguru, gepeng, mansion, botol, balap, sempurnakan, taruh	0,2352
35	juta, penerima, orang, capai, target, tercapai, manfaat, digenjot	0,6286

3.2 Topic Refinement and Selection

After the topic modeling stage, the next step was to refine the results through the selection of topics relevant to the MBG Program. This process aims to ensure that the topics used in further analysis accurately represent issues related to the program.

Topic selection was conducted manually based on the interpretation of top terms in each topic. This approach was adopted because topic coherence does not always reflect the clarity of topic meaning, especially in short-text data such as tweets, where word co-occurrence tends to be limited. Therefore, the selection process focused on whether the top terms form a meaningful and relevant discussion within the context of the MBG Program.

The selection results show that out of the initial 36 topics, 18 topics were considered relevant for further analysis. Topics that did not demonstrate clear relevance or did not form interpretable issues were excluded. In this process, it was observed that topic coherence does not always align with topic relevance. Some topics with low coherence values were retained because they conveyed clear meaning. For example, a topic with top terms "proyek, korupsi, rakyat, ladang, penguasa, makanbergizigratis, pemerintah, berjamaah" was retained as it represents issues related to corruption in program implementation. In contrast, some topics with high coherence values were excluded due to a lack of relevance to the MBG Program.

After the selection process, the topic quality was re-evaluated. The results indicate that topic coherence increased from 0.4446 to 0.5370, while topic diversity improved from

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0.8541 to 0.8611. These improvements indicate that the selected topics exhibit stronger word associations and higher diversity compared to the initial set. The selected topics along with their top terms and coherence values are presented in Table 6.

Table 6. Selected Topics After Relevance Filtering

Topic Reduced	Top Terms	Coherence (c_v)
0	makanbergizigratis, program, keracunan, lanjutkan, anak, indonesia, gizi, rakyat	0,4022
1	aparatkeamanan, unitpelaksana, jaga, langkah, kualitasmakanan, semangat, bangga, program	0,7869
2	makan, menu, basi, makanbergizigratis, anak, lauk, makanan, enak	0,4844
3	unitpelaksana, aktordaerah, aktorlokal, menu, ulat, dapur, temuan, siswa	0,3992
4	makanbergizigratis, maaf, menolak, hubungan, pres, memaksakan, beresin, ego	0,4153
5	kasuskeracunan, dianiaya, wartawan, pasar, terulang, diduga, meliput, liput	0,5972
8	susu, liter, telur, kotak, dimakan, cm, nasi, makan	0,3055
9	dapur, pimpinan, daerah3t, dibangun, umkm, makanbergizigratis, bangkit, hukum	0,2700
12	proyek, korupsi, rakyat, ladang, penguasa, makanbergizigratis, pemerentah, berjamaah	0,3517
13	kerja, lapangan, job, lowongan, luas, peluang, melimpah, terbuka	0,3189
16	papua, tokoh, adat, program, anakanak, tanahpapua, mendukung, cerdas	0,5643
18	anaksekolah, anakanak, sekolah, anak, stunting, uda, menyasar, ngasih	0,3548
20	harga, ayam, stok, telur, pakan, singkong, permintaan, ngeluh	0,4634
24	babi, minyak, mengandung, tray, nampan, food, halal, impor	0,9583
25	koordinasi, tim, rapat, rutin, bentuk, sense, solid, disiplin	0,6559
28	aktorlokal, wakil, kepala, pemukulan, sidak, petugas, unitpelaksana, polisi	0,7459
33	nasi, ayam, tumis, menu, jeruk, kacang, goreng, disajikan	0,9635
35	juta, penerima, orang, capai, target, tercapai, manfaat, digenjot	0,6286

3.3 Aspect Identification

After the topic selection process, the next step is to identify aspects from each selected topic. This process aims to provide a clearer representation of the issues discussed in each topic, enabling aspect-level sentiment analysis (Aspect-Based Sentiment Analysis).

Aspect identification was performed through a semi-automated aspect naming process using a Large Language Model (LLM), namely ChatGPT. At this stage, the list of top terms for each topic was used as input to generate concise aspect names that are aligned with the discussion context.

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The generated aspect names were then manually verified to ensure consistency between the aspect labels and the underlying topic meanings. Adjustments were made when necessary to obtain the most representative aspect names.

Through this process, each selected topic was mapped into a more structured set of aspects, allowing sentiment analysis to be conducted more specifically for each issue discussed. The list of identified aspects is presented in Table 7.

Table 7. List of Identified Aspects

Topic Reduced	Aspect Name	Number of Tweets
0	Sentimen Umum terhadap MBG	5,478
1	Pelibatan Aparat Keamanan dalam Implementasi MBG	175
2	Kualitas Makanan MBG	162
3	Temuan Lapangan MBG	153
4	Penolakan Publik terhadap MBG	102
5	Insiden Keracunan dan Sorotan Media pada Program MBG	91
8	Kandungan Gizi dan Porsi MBG	73
9	Infrastruktur dan Tata Kelola MBG	69
12	Risiko Korupsi MBG	61
13	Dampak Lapangan Kerja	60
16	Dukungan Sosial MBG di Papua	48
18	Sasaran Anak Sekolah	35
20	Dampak MBG terhadap Harga Pangan	33
24	Isu Halal MBG	28
25	Koordinasi Pelaksanaan MBG	25
28	Pengawasan dan Penindakan Lapangan	23
33	Penyajian Menu MBG	19
35	Cakupan dan Target Penerima MBG	16
	Total	**6,651**

3.4 Sentiment Distribution Across Aspects

After sentiment labeling was completed, the next step was to analyze the distribution of sentiment across the identified aspects. This analysis aims to examine patterns of public opinion regarding the MBG Program across different aspects. The aggregated sentiment results in terms of tweet counts for each aspect are presented in Table 8, while the percentage distribution is shown in Table 9.

Table 8. Sentiments Counts per Aspect

Aspect Name	Positive	Neutral	Negative	Total
Dukungan Sosial MBG di Papua	48	0	0	48
Pelibatan Aparat Keamanan dalam Implementasi MBG	146	15	14	175
Dampak Lapangan Kerja	50	3	7	60
Penyajian Menu MBG	14	0	5	19
Koordinasi Pelaksanaan MBG	18	7	0	25
Infrastruktur dan Tata Kelola MBG	35	19	15	69
Temuan Lapangan MBG	76	24	53	153
Sasaran Anak Sekolah	14	6	15	35
Sentimen Umum terhadap MBG	2058	785	2635	5.478
Cakupan dan Target Penerima MBG	5	11	0	16

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Aspect Name	Positive	Neutral	Negative	Total
Pengawasan dan Penindakan Lapangan	5	3	15	23
Insiden Keracunan dan Sorotan Media pada Program MBG	19	8	64	91
Isu Halal MBG	5	4	19	28
Penolakan Publik terhadap MBG	18	36	48	102
Kandungan Gizi dan Porsi MBG	9	15	49	73
Risiko Korupsi MBG	6	1	54	61
Kualitas Makanan MBG	15	37	110	162
Dampak MBG terhadap Harga Pangan	0	0	33	33
Total				**6,651**

Table 9. Sentiment Percentage per Aspect

Aspect Name	Positif (%)	Netral (%)	Negatif (%)
Dukungan Sosial MBG di Papua	100.00	0.00	0.00
Pelibatan Aparat Keamanan dalam Implementasi MBG	83.43	8.57	8.00
Dampak Lapangan Kerja	83.33	5.00	11.67
Penyajian Menu MBG	73.68	0.00	26.32
Koordinasi Pelaksanaan MBG	72.00	28.0	0.00
Infrastruktur dan Tata Kelola MBG	50.72	27.54	21.74
Temuan Lapangan MBG	49.67	15.69	34.64
Sasaran Anak Sekolah	40.00	17.14	42.86
Sentimen Umum terhadap MBG	37.56	14.33	48.10
Cakupan dan Target Penerima MBG	31.25	68.75	0.00
Pengawasan dan Penindakan Lapangan	21.74	13.04	65.22
Insiden Keracunan dan Sorotan Media pada Program MBG	20.88	8.79	70.33
Isu Halal MBG	17.86	14.29	67.86
Penolakan Publik terhadap MBG	17.65	35.29	47.06
Kandungan Gizi dan Porsi MBG	12.33	20.55	67.12
Risiko Korupsi MBG	9.84	1.64	88.52
Kualitas Makanan MBG	9.26	22.84	67.90
Dampak MBG terhadap Harga Pangan	0.00	0.00	100.00

Based on the sentiment distribution, each aspect exhibits different patterns of public opinion. Some aspects are dominated by positive sentiment, while others show a predominance of negative sentiment, reflecting public concerns and criticisms regarding the implementation of the program.

The aspects with the highest positive sentiment include Dukungan Sosial MBG di Papua (100%), Pelibatan Aparat Keamanan dalam Implementasi MBG (83.43%), and Dampak Lapangan Kerja (83.33%). These findings indicate that, in these aspects, the MBG Program is generally perceived positively by the public, particularly in terms of social support and economic benefits.

In contrast, the aspects with the highest negative sentiment are Dampak MBG terhadap Harga Pangan (100%), Risiko Korupsi MBG (88.52%), and Insiden Keracunan dan Sorotan Media pada Program MBG (70.33%). These results suggest that public concerns are primarily related to economic impacts, governance transparency, and food safety issues in the implementation of the MBG Program.

Overall, the results indicate that public opinion on the MBG Program varies and is influenced by the aspects being discussed. The aspect-based approach enables a more

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specific identification of issues compared to sentiment analysis at the overall text level, thereby providing a more comprehensive understanding of public perception.

3.5 Word Cloud Visualization Based on Sentiment Categories

To provide a visual representation of dominant words in each sentiment category, a word cloud method is applied based on the results of sentiment classification. This visualization is constructed from tweets that have been grouped into three categories, namely positive, neutral, and negative. The size of each word in the word cloud represents its frequency of occurrence within each category, so larger words indicate higher frequency. Figure 2 presents the word cloud visualization for the three sentiment categories.

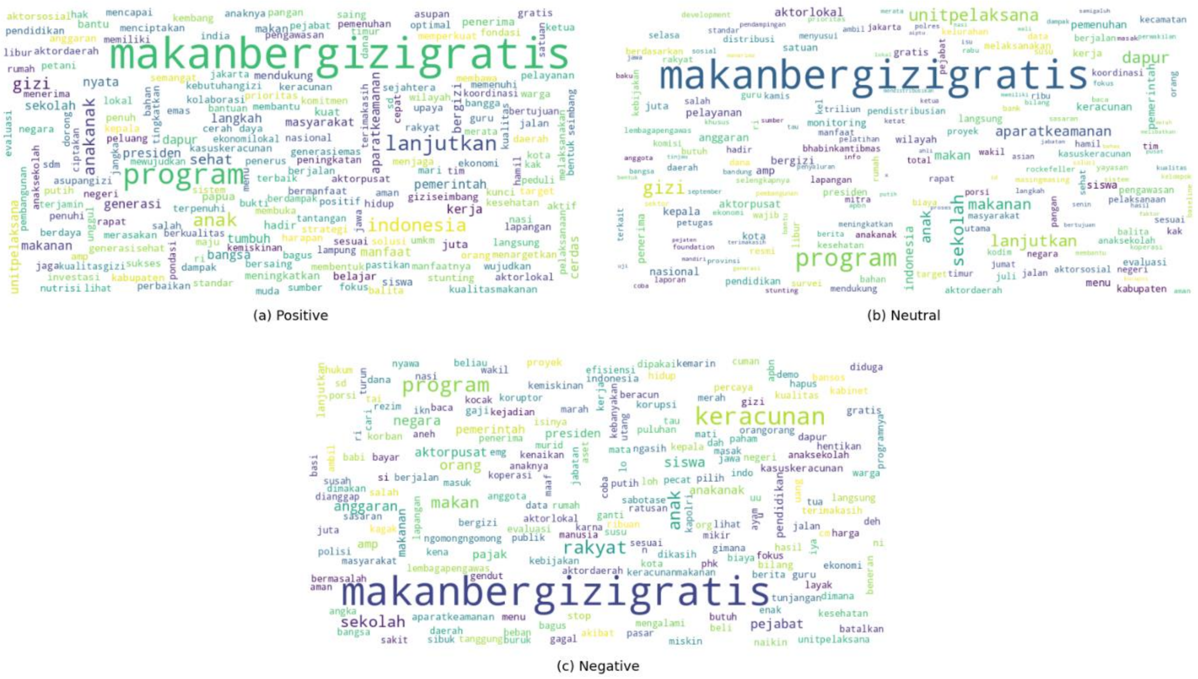

Figure 2. Word Cloud Visualization Based on Sentiment Categories

3.6 Discussions

The results of this study indicate that public opinion on the MBG Program varies and is influenced by the aspects being discussed. Aspects related to social and economic benefits, such as social support in Papua and employment impact, tend to be dominated by positive sentiment. This suggests that the MBG Program is perceived as providing tangible benefits in improving public welfare, particularly in regions that require nutritional intervention.

In contrast, aspects related to program implementation are dominated by negative sentiment. Issues such as rising food prices, potential corruption, and food poisoning incidents emerge as major public concerns. These findings reflect public apprehension regarding governance, transparency, and the quality of program implementation in practice. Therefore, although the program has positive objectives, its success largely depends on effective and accountable implementation.

These findings are consistent with the study by [6] which reported that public sentiment toward the MBG Program tends to be dominated by negative sentiment. However, their study analyzed sentiment only at the overall text level, limiting the ability

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to identify specific aspects driving such sentiment. Similarly, [7] applied a topic modeling approach to identify discussion topics but did not incorporate sentiment analysis at the aspect level.

In contrast to previous studies, this research integrates Aspect-Based Sentiment Analysis (ABSA) with BERTopic-based aspect extraction, enabling a more fine-grained analysis of public opinion. This approach not only reveals general sentiment trends but also identifies specific aspects that serve as sources of public support and indications of opposition toward the MBG Program.

Thus, this study contributes by providing a more structured and in-depth mapping of public opinion. The findings do not only indicate whether a policy is supported or criticized but also explain which specific aspects drive such responses. This information is valuable as a basis for consideration in data-driven policy evaluation, allowing improvements to be focused on the aspects that receive the most public attention.

4. CONCLUSION

This study successfully analyzes public opinion on the Free Nutritious Meal (MBG) Program on the X platform using an Aspect-Based Sentiment Analysis (ABSA) approach with BERTopic-based aspect extraction. The proposed approach identifies 36 initial topics, which are further refined into 18 relevant aspects, accompanied by an improvement in topic quality as indicated by the topic coherence and topic diversity scores. The results show that public opinion on the MBG Program varies and is influenced by the aspects being discussed.

In general, aspects related to social and economic benefits tend to receive positive sentiment, while aspects related to program implementation, such as food quality, corruption risk, and the impact on food prices, are dominated by negative sentiment. These findings indicate that the success of the MBG Program is determined not only by policy objectives but also by the quality of its implementation in practice.

Based on the aspects with the highest dominance of negative sentiment, the findings of this study can serve as a consideration for the evaluation and improvement of the MBG Program. The dominance of negative sentiment in the aspect of the impact of MBG on food prices indicates public concerns regarding price increases and the availability of food commodities in the market. This finding highlights the importance of more coordinated food procurement and distribution planning, as well as appropriate price stabilization policies, to ensure that program implementation does not impose additional economic burdens on the public.

The dominance of negative sentiment in the aspect of MBG corruption risk indicates public concerns regarding transparency in program budget management. This finding emphasizes the importance of improving transparency in budget management through the regular publication of implementation reports and strengthening oversight systems, thereby enhancing public trust in the program.

Meanwhile, the dominance of negative sentiment in the aspect of poisoning incidents and media attention reflects public concern regarding food safety in program implementation. This finding underscores the importance of consistent food safety standards, regular quality inspections, and prompt response procedures in the event of incidents in the field. Thus, aspect-based analysis not only maps public perception but also provides more targeted inputs for policy improvement.

The main contribution of this study lies in the integration of ABSA with BERTopic, enabling a more fine-grained analysis of public opinion compared to conventional approaches that only examine sentiment at the overall text level. This approach provides a more structured mapping of public opinion and identifies specific aspects that drive both public support and indications of opposition.

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This study has several limitations. The use of short-text data from the X platform may affect the quality of topic modelling, particularly in terms of coherence. In addition, variations in language usage within tweets may influence the sentiment labelling results.

For future research, it is recommended to integrate data from multiple social media platforms to obtain a more comprehensive understanding of public opinion. Furthermore, developing sentiment classification models tailored to specific topics may help improve the quality of analysis.

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