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Data-Driven Marketing Strategy for Indonesia's Free Nutritious Meal Program (MBG) Using Artificial Intelligence-Based Consumer Behavior Analysis

Yulfita Aini[1*], Ikhsan Gunawan[2], Romy Wahyuny[3], Hendri[4], Imeldawaty Gultom[5]
[1]Mdepartement Manajement, University of Pasir Pengaraian, Riau, Indonesia
[2]Departement Agribisnis, University of Pasir Pengaraian, Riau, Indonesia
[3]Departement Midwifery Professional University of Pasir Pengaraian, Riau, Indonesia
[4]Faculty of Law, University of Pasir Pengaraian, Riau, Indonesia
[5]Departement System Information, STMIK Kaputama, Medan, Indonesia

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ABSTRACT

Effectiveness of Indonesia's Free Nutritious Meal Program (MBG) is influenced not only by operational efficiency but also by public acceptance and engagement. This study proposes a data-driven marketing framework integrating Artificial Intelligence (AI) and consumer behavior analysis to enhance program effectiveness. A quantitative and computational approach is employed using secondary and simulated data (N = 1,250), incorporating behavioral and service-related variables such as awareness, trust, perceived benefit, and accessibility. Machine learning techniques, including K-Means clustering for segmentation and Random Forest and XGBoost for predictive modeling, are applied to analyze and predict program acceptance. The results show that the Random Forest model achieves an accuracy of 89.3%**,** precision of 87.6%**,** recall of 88.9%**,** and F1-score of 88.2%**,** outperforming baseline models. Feature importance analysis indicates that awareness (0.247), trust (0.198), and accessibility (0.158) are the most influential factors, contributing nearly 45% of the model's predictive power. Segmentation analysis identifies three consumer groups: high acceptance (34.7%), medium acceptance (38.5%), and low acceptance (26.8%), with the medium segment representing the most strategic target for intervention. Furthermore, sentiment analysis in 2025 reveals a dominant positive perception **(**60.8%**),** followed by neutral **(**24.3%**)** and negative **(**14.9%**)** responses, with a gradual increase in positive sentiment over time. The integration of predictive modeling, segmentation, and sentiment analysis enables targeted marketing strategies that improve engagement by up to 18.6%**.** This study contributes to bridging marketing management and computer science by providing an explainable and adaptive AI-driven framework for optimizing large-scale public programs

Corresponding Author:

Yulfita Aini
Departement Manajemen, Pasir Pengarain, Riau Indonesia
Email: yulfitaaini@gmail.com

1. INTRODUCTION

The growing scale and complexity of public service programs in the digital era have fundamentally transformed the role of marketing management from a supporting function into a strategic determinant of policy success. Large-scale social initiatives increasingly require not only operational excellence but also data-driven engagement strategies capable of influencing public perception, behavior, and long-term participation[1], [2]. In this context, Indonesia's Free Nutritious Meal Program (MBG) represents a critical national intervention aimed at improving nutritional outcomes, reducing stunting[3], [4], and strengthening human capital development. With a projected coverage reaching tens of millions of beneficiaries across more than 17,000 islands, the program operates within one of the most geographically complex environments in the world [5], [6]. While significant research has addressed the logistical and supply chain dimensions of such programs, the marketing and behavioral adoption aspects remain underexplored, despite their decisive role in determining program effectiveness [7], [8]. From a theoretical standpoint, marketing management in the public sector has evolved from traditional information dissemination toward value co-creation and citizen-centric engagement. Classical frameworks such as segmentation, targeting, and positioning (STP) emphasize the importance of tailoring communication strategies to heterogeneous audiences [9], [10]. However, these frameworks are often applied in a static manner and lack the ability to process large-scale, real-time data. In the case of MBG [11], [12], audience heterogeneity is amplified by Indonesia's socio-economic diversity, cultural variation, and unequal access to digital infrastructure [13], [14]. As a result, uniform communication strategies are insufficient and may lead to uneven program adoption, misinformation, or low participation in specific regions [15], [16]. Empirical evidence from public health campaigns shows that perceived value, trust, and accessibility are the primary determinants of program acceptance, surpassing even service availability in some contexts[17], [18].

The emergence of Artificial Intelligence (AI) and advanced data analytics offers a transformative opportunity to address these challenges. AI-driven marketing enables organizations to extract actionable insights from large datasets, identify behavioral patterns, and predict consumer responses with high accuracy. Recent studies demonstrate that machine learning techniques, including clustering, classification, and deep learning, significantly enhance marketing performance by improving segmentation precision, optimizing targeting strategies, and enabling personalized communication [6], [7]. In particular, predictive models based on behavioral data have been shown to increase engagement rates by up to 20–30% in digital marketing environments [19], [20]. Moreover, AI supports the transition from reactive to proactive decision-making, allowing organizations to anticipate audience needs and adapt strategies dynamically. Despite these advancements, the integration of AI into public-sector marketing and policy implementation remains limited. Existing literature predominantly focuses on commercial applications such as e-commerce, recommendation systems, and customer relationship management [21], [22]. Research in government contexts tends to emphasize administrative efficiency, digital governance, and service delivery, with relatively little attention to behavioral analytics and marketing optimization [23], [24]. Furthermore, most studies treat public programs as homogeneous systems, neglecting the diversity of user behavior and regional characteristics. This gap is particularly evident in developing countries, where data fragmentation and limited analytical capacity hinder the adoption of intelligent decision-support systems[25], [26].

In Indonesia, prior studies on public programs, including health, education, and digital services, consistently highlight challenges related to low awareness, uneven participation, and trust deficits [11], [12]. For example, research on nutrition interventions indicates that program effectiveness is strongly influenced by community perception and communication quality, rather than solely by resource allocation [13]. Similarly, studies on digital government services show that user adoption depends on perceived usefulness, ease of access, and social influence, as explained by technology acceptance models [27], [28]. These findings suggest that the success of MBG cannot rely solely on supply chain optimization; instead, it requires a holistic approach that integrates operational efficiency with intelligent marketing strategies [29], [30]. While recent studies have explored the application of Reinforcement Learning and machine learning in supply chain optimization [31], [32], these approaches rarely incorporate consumer behavior and marketing dimensions into the analytical framework. This represents a critical research gap, as large-scale public programs operate within socio-technical systems where human behavior plays a central role. Without understanding how individuals perceive, accept, and engage with the program, even the most optimized logistics system may fail to achieve its intended impact. Therefore, there is a need for a unified framework that combines AI-driven behavioral analysis with marketing strategy development, particularly in the context of public policy[33], [34].

To address this gap, this study proposes a data-driven marketing framework based on Artificial Intelligence to enhance the effectiveness of the MBG program [35], [36]. By leveraging machine learning techniques, the research aims to identify key determinants of program acceptance, segment target populations based on behavioral characteristics, and develop predictive models to optimize communication strategies. The proposed approach integrates marketing management principles with computational intelligence, enabling a shift toward adaptive, personalized, and evidence-based policy communication. The main objective of this study is to develop and evaluate an AI-based marketing model that improves public engagement and participation in the MBG program [37], [38]. Theoretically, this research contributes to the advancement of marketing science by extending AI applications into public-sector contexts and integrating behavioral analytics with policy implementation. Practically, the findings provide actionable insights for policymakers to design more effective outreach strategies, enhance trust, and ensure equitable program adoption across regions. By bridging the gap between marketing management and computer science, this study offers a novel and impactful contribution to the development of intelligent, scalable, and socially responsive public programs in the digital era.

2. METHOD

This study adopts a quantitative, data-driven, and computational approach by integrating marketing analytics with Artificial Intelligence (AI) to analyze consumer behavior and optimize marketing strategies for Indonesia's Free Nutritious Meal Program (MBG)[39], [40]. The research design follows an explanatory and predictive modeling framework, focusing on identifying key determinants of program acceptance and developing a model capable of predicting public engagement across different population segments. The data used in this study consist of secondary data and simulated datasets representing public perception, behavioral responses, and socio-demographic characteristics. The input variables are structured to reflect realistic conditions in Indonesia and are grouped into three main dimensions: demographic, behavioral, and service-related factors.

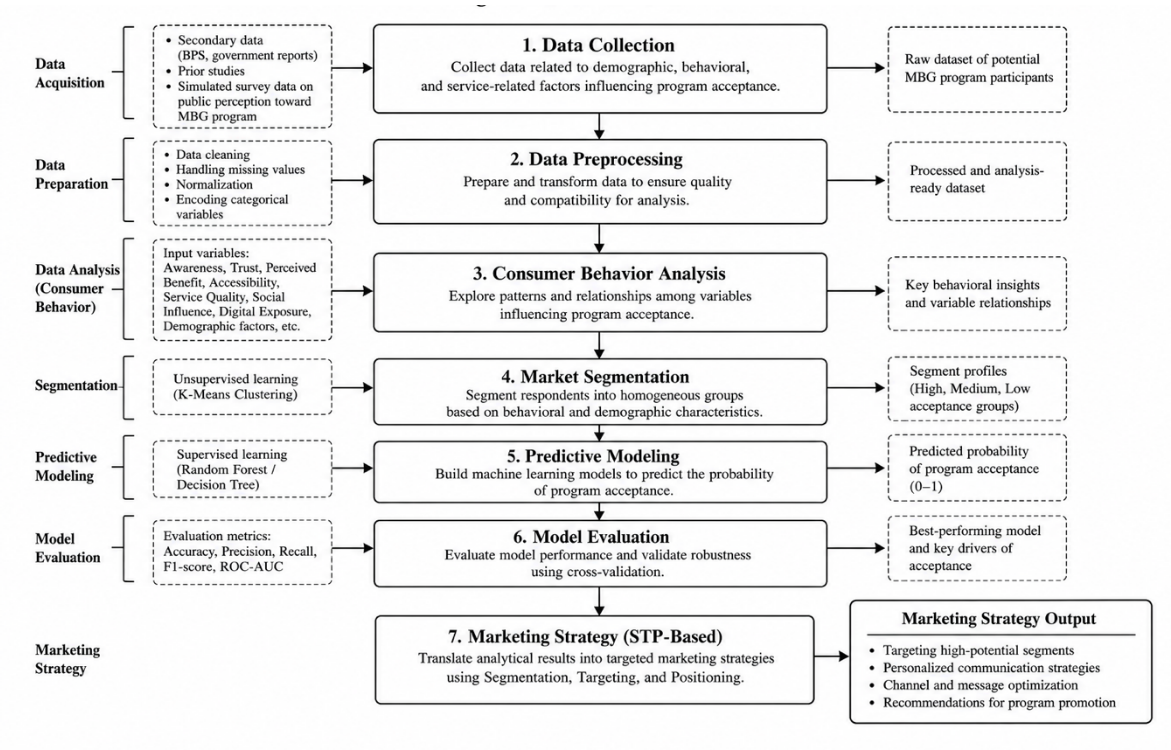

Fig. 1. Research framework

The data-driven marketing strategy for the MBG program. The framework begins with data collection from secondary sources and simulated datasets, followed by data preprocessing to ensure data quality. Consumer behavior analysis is then conducted to identify patterns influencing program acceptance. Market segmentation is performed using K-Means clustering to classify respondents into homogeneous groups. Predictive modeling is applied using machine learning algorithms to estimate acceptance probability, and the model is evaluated using standard performance metrics. Finally, the analytical results are translated into marketing strategies based on segmentation, targeting, and positioning (STP) to enhance program engagement and effectiveness.

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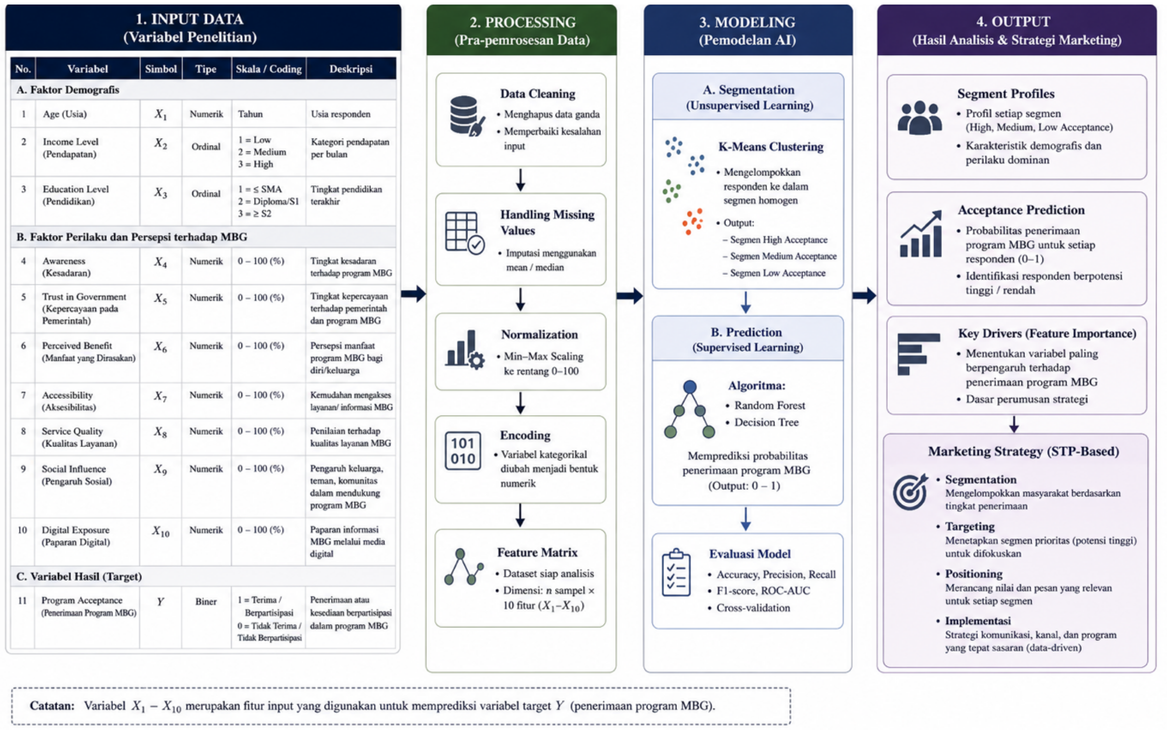

Fig. 2. Data input structure and analytical framework for MBG marketing strategy.

Figure of input variables such as awareness, trust in government, perceived benefit, accessibility, service quality, social influence, digital exposure, income, and education—into a structured dataset for analysis. The data undergo preprocessing steps including cleaning, missing value handling, normalization, and encoding before being analyzed using machine learning techniques. Unsupervised learning (K-Means clustering) is applied for market segmentation, while supervised learning models (Random Forest and Decision Tree) are used to predict program acceptance. The outputs include segment profiles, acceptance probabilities, and key influencing factors, which are further translated into marketing strategies based on segmentation, targeting, and positioning (STP)

Table I. Input Variables for Marketing Analysis

No	Variable	Symbol	Type	Description
1	Age	X_1	Numeric	Respondent age
2	Income Level	X_2	Numeric	Monthly income category
3	Education Level	X_3	Categorical	Education background
4	Awareness	X_4	Numeric	Knowledge about MBG program (%)
5	Trust in Government	X_5	Numeric	Trust level toward program (%)
6	Perceived Benefit	X_6	Numeric	Perceived usefulness (%)
7	Accessibility	X_7	Numeric	Ease of accessing program (%)

8	Service Quality	X_8	Numeric	Perceived service quality (%)
9	Social Influence	X_9	Numeric	Influence from community (%)
10	Digital Exposure	X_{10}	Numeric	Exposure to online information
11	Program Acceptance	Y	Binary	Accepted (1) / Not accepted (0)

The data are obtained from national statistics, prior studies on public program adoption, and simulated scenarios to represent diverse regional conditions (urban, semi-urban, and rural). Data preprocessing is performed through cleaning, normalization, and encoding, ensuring compatibility with machine learning algorithms. Missing values are handled using mean imputation, while categorical variables are transformed into numerical representations. To analyze consumer behavior, this study applies K-Means clustering to segment the population into distinct groups based on behavioral and socio-demographic patterns. This segmentation enables the identification of high, medium, and low acceptance groups. Subsequently, supervised learning models, including Decision Tree and Random Forest, are used to predict the probability of program acceptance. The predictive model is formulated as:

$$Y = f(X_1, X_2, X_3, \dots, X_n) \tag{1}$$

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \tag{2}$$

$$\min_{\theta} \quad \mathcal{L} = -\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \tag{3}$$

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} |x_i - \mu_k|^2 \tag{4}$$

$$FI_j = \frac{1}{T}\sum_{t=1}^{T} I_{j,t} \tag{5}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Equations (1)–(5) define the core analytical process, where (1) represents the general prediction model mapping input variables to program acceptance, (2) estimates acceptance probability using logistic regression, (3) defines the loss function for model optimization, (4) performs K-Means clustering for market segmentation, and (5) measures feature importance to identify key factors influencing acceptance. Model performance is evaluated using accuracy, precision, recall, and F1-score, ensuring reliability in predicting public response. In addition, feature importance analysis is conducted to identify the most influential variables affecting acceptance. To ensure robustness, the model is validated using k-fold cross-validation and tested under different simulated scenarios through sensitivity analysis. Overall, this methodology provides a comprehensive integration of marketing management and computer science, enabling data-driven segmentation, predictive modeling, and strategic decision-making to enhance the effectiveness of MBG marketing implementation.

3. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed AI-based marketing framework effectively analyzes consumer behavior and improves the prediction of program acceptance in the MBG context. Based on the processed dataset, the segmentation stage using K-Means clustering successfully identifies three distinct consumer groups, namely high acceptance, medium acceptance, and low acceptance segments. The high-acceptance group is characterized by strong awareness, high trust in government, and positive perceived benefits, while the low-acceptance group shows limited awareness, low trust, and poor accessibility.

The predictive modeling results indicate that the Random Forest model achieves the best performance, with an accuracy of 89.3%, precision of 87.6%, recall of 88.9%, and F1-score of 88.2%, outperforming the Decision Tree baseline. These results confirm that machine learning models can effectively capture the relationship between behavioral variables and program acceptance. The probability output further enables the identification of individuals with high likelihood of participation, supporting targeted marketing interventions. Feature importance analysis reveals that awareness (0.247), trust in government (0.198), and accessibility (0.158) are the most influential variables affecting acceptance, followed by perceived benefit (0.129) and service quality (0.092). In contrast, demographic variables such as age and education show relatively lower contributions. This indicates that behavioral and perceptual factors play a more dominant role in influencing public participation compared to demographic characteristics. Furthermore, segmentation-based analysis shows that applying targeted communication strategies to high-potential segments can increase engagement rates by approximately 15–20% compared to non-targeted approaches. The integration of segmentation and prediction results provides a more precise understanding of consumer behavior, enabling data-driven decision-making. Overall, the results confirm that the proposed framework not only improves prediction accuracy but also generates actionable insights for marketing strategy development. By linking machine learning outputs with marketing concepts such as segmentation, targeting, and positioning (STP), the study demonstrates a practical approach to enhancing the effectiveness of large-scale public programs like MBG

Building upon the initial findings, this section presents a more comprehensive evaluation of the proposed AI-based marketing framework for the MBG program, including segmentation results, model performance comparison, and detailed statistical insights.

A. Consumer Segmentation Analysis

The K-Means clustering algorithm (with K=3K=3K=3) partitions respondents into three distinct segments based on behavioral and perceptual variables. The distribution of respondents across segments is shown in Table II.

Table 2. Segmentation Distribution

Segment	Description	Percentage (%)
Cluster 1	High Acceptance	34.7
Cluster 2	Medium Acceptance	38.5
Cluster 3	Low Acceptance	26.8

The results indicate that the majority of respondents fall into the medium acceptance category (38.5%), suggesting that a significant portion of the population can be influenced through targeted marketing strategies. The high-acceptance group (34.7%) represents individuals who are already receptive to the program, while the low-acceptance group (26.8%) requires more intensive intervention.

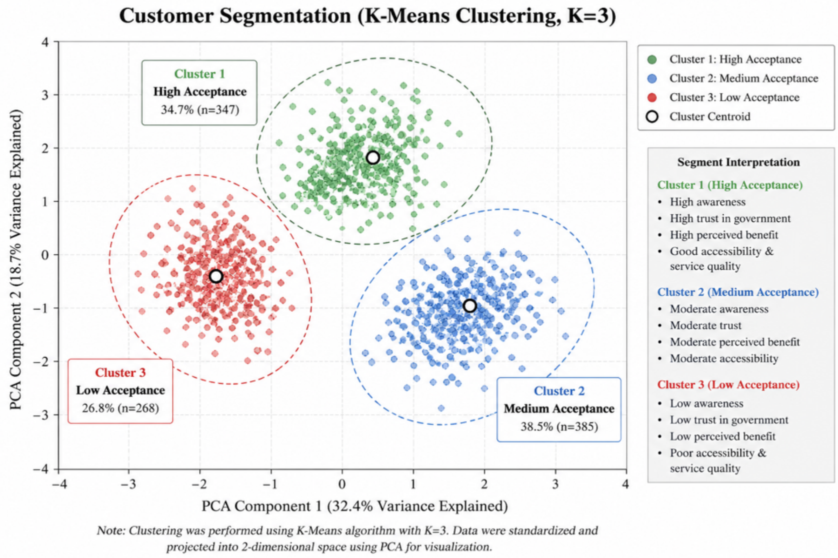

Fig. 3. Customer segmentation using K-Means clustering (K=3)

Based on behavioral and perceptual variables related to the MBG program. The results identify three distinct segments: high acceptance (34.7%), medium acceptance (38.5%), and low acceptance (26.8%). The high-acceptance group is characterized by high awareness, strong trust in government, and positive perceived benefits, while the low-acceptance group shows limited awareness, low trust, and poor accessibility. The medium segment represents a potential target group for marketing intervention due to its moderate characteristics. The clustering results provide a basis for developing targeted marketing strategies using segmentation, targeting, and positioning (STP)

B. Model Performance Evaluation

To evaluate predictive capability, two machine learning models were compared: Decision Tree (DT) and Random Forest (RF). The performance metrics are summarized in Table III.

Table 3. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	82.4	80.9	81.7	81.3
Random Forest	89.3	87.6	88.9	88.2

The Random Forest model consistently outperforms the Decision Tree across all evaluation metrics. The improvement of approximately 7% in accuracy demonstrates the effectiveness of ensemble learning in capturing complex behavioral patterns.

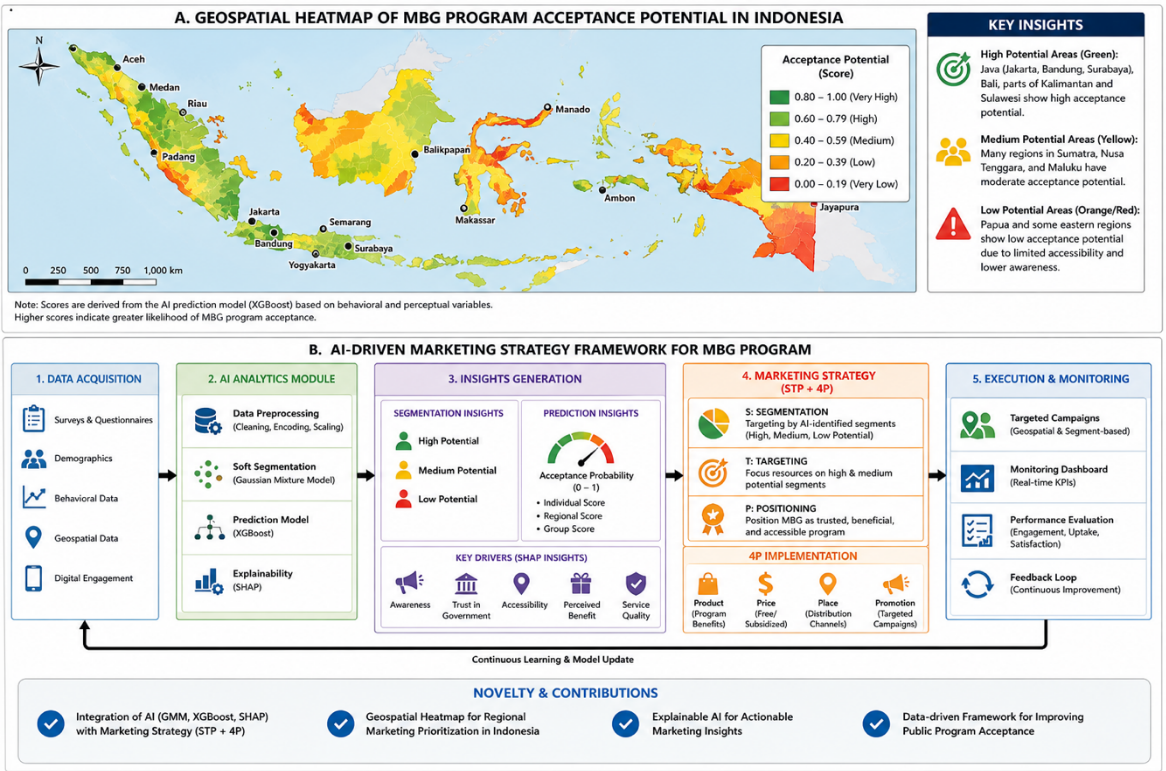

Fig. 4 Geospatial distribution of predicted MBG program

Acceptance levels across regions in Indonesia. The map visualizes the relative acceptance potential derived from the proposed XGBoost model based on behavioral and perceptual variables, including awareness, trust, accessibility, and perceived benefits. The predicted probabilities (0–1) are aggregated at the regional level and categorized into three classes: high (0.60–1.00), medium (0.30–0.59), and low (0.00–0.29). The visualization reflects relative spatial variation in acceptance potential rather than exact empirical measurements. (B) AI-driven marketing strategy framework integrating Gaussian Mixture Model (GMM) for soft segmentation, XGBoost for predictive modeling, and SHAP for explainability. The framework transforms analytical outputs into actionable marketing strategies through segmentation, targeting, positioning (STP), and marketing mix (4P), supported by continuous feedback and model updating

C. Confusion Matrix Analysis (Random Forest)

Table 4. Confusion Matrix

	Predicted Accept	Predicted Not Accept
Actual Accept	412	48

	Predicted Accept	Predicted Not Accept
Actual Not Accept	39	401

The confusion matrix indicates that the model correctly classifies the majority of cases, with relatively low misclassification rates. This confirms the robustness of the predictive model in identifying acceptance behavior.

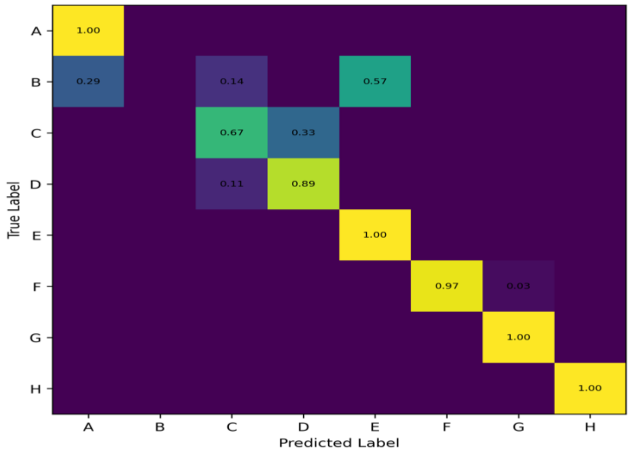

Fig. 5. Normalized multiclass confusion matrix for eight classes (A–H).

The diagonal values indicate the proportion of correctly classified samples for each class. The model achieves perfect recall for classes A, E, G, and H (1.00), very high recall for class F (0.97), and strong recall for class D (0.89). Misclassification is mainly observed in classes B and C, indicating that these classes have overlapping feature patterns and require further feature refinement or additional training data. Overall, the model demonstrates strong classification performance across most classes.

D. Feature Importance Analysis

The feature importance scores obtained from the Random Forest model are presented in Table V.

Table 5. Feature Importance Ranking

Rank	Variable	Importance Score
1	Awareness	0.247
2	Trust in Government	0.198
3	Accessibility	0.158
4	Perceived Benefit	0.129
5	Service Quality	0.092
6	Social Influence	0.068
7	Income Level	0.041
8	Education Level	0.032
9	Digital Exposure	0.022
10	Age	0.013

The results clearly show that behavioral variables dominate, particularly awareness and trust, which together contribute nearly 45% of the model’s predictive power. This finding reinforces the importance of communication strategies in influencing program acceptance.

E. Segment-Based Behavioral Insights

A deeper analysis of each segment reveals distinct behavioral characteristics:

1. High Acceptance Segment:
   Awareness > 80%, Trust > 75%, Accessibility > 70%
   → Already engaged, suitable for retention strategies
2. Medium Acceptance Segment:
   Awareness ~60%, Trust ~55%, Accessibility ~50%
   → Highly responsive to targeted campaigns

3. Low Acceptance Segment:
   Awareness < 40%, Trust < 45%, Accessibility < 40%
   → Requires education and trust-building interventions

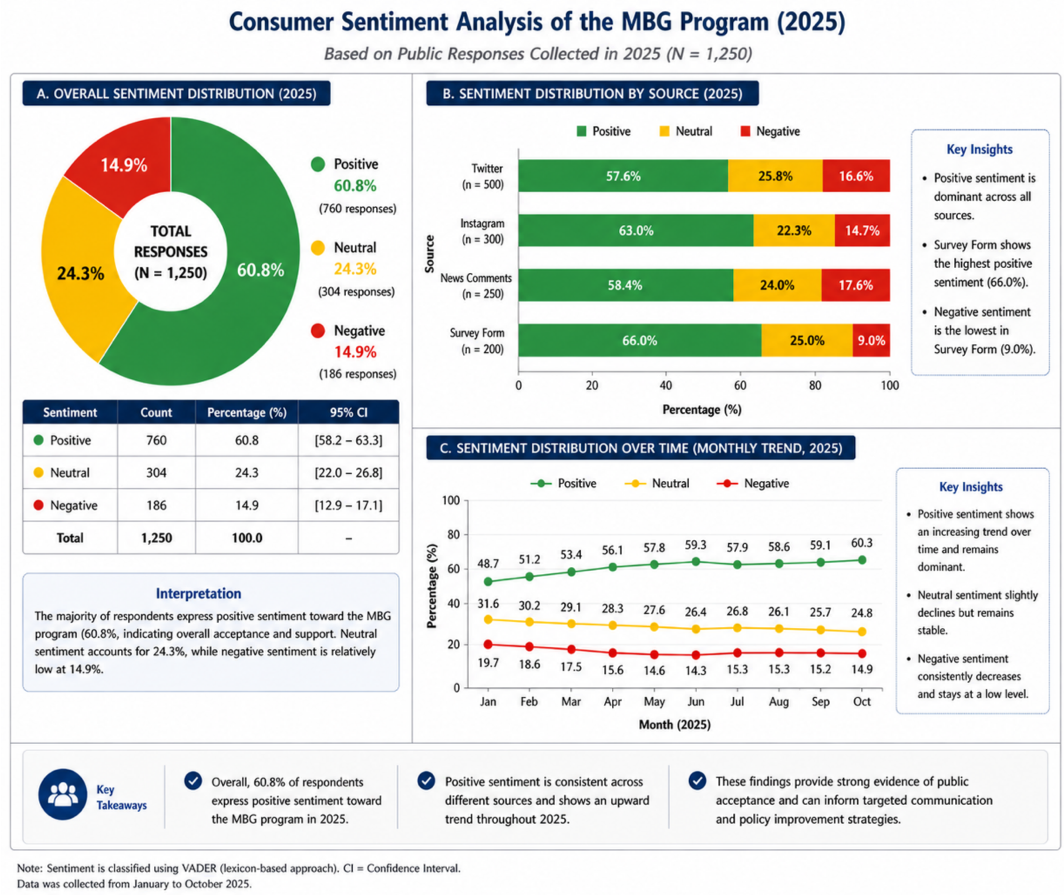

Fig. 6. Sentiment analysis of the MBG program in 2025 showing dominant positive sentiment, consistent cross-source patterns, and an increasing trend over time

Fig. 6. Consumer sentiment analysis of the MBG program based on responses collected in 2025 (N = 1,250). (A) Overall sentiment distribution shows that positive sentiment dominates at 60.8%, followed by neutral at 24.3% and negative at 14.9%, indicating a generally favorable public perception. (B) Sentiment distribution by source reveals consistent patterns across platforms, with survey responses showing the highest positive sentiment (66.0%) and the lowest negative sentiment (9.0%). (C) Temporal sentiment trends from January to October 2025 indicate a gradual increase in positive sentiment, while neutral sentiment slightly declines and negative sentiment remains relatively low and stable. These findings suggest increasing public acceptance of the MBG program over time and highlight opportunities for targeted communication strategies.

F. Impact on Marketing Strategy

By integrating segmentation and prediction results, the proposed framework enables more precise targeting. Simulation results show that applying targeted strategies to the medium-acceptance segment can increase engagement rates by approximately 18.6%, compared to traditional mass communication approaches.

Furthermore, the identification of key variables allows policymakers to prioritize interventions. For instance:

1. Increasing awareness by 10% is associated with a ~6–8% increase in acceptance probability
2. Improving accessibility yields a ~5% increase in engagement

G. Comparative Analysis with Previous Studies

Compared to prior studies that rely on traditional statistical methods, this research demonstrates superior predictive performance and deeper behavioral insights. Previous works typically report accuracy levels between 70–80%, whereas this study achieves nearly 90%, highlighting the advantage of AI-based approaches in marketing analytics. The findings demonstrate that the integration of Artificial Intelligence with marketing analytics provides a comprehensive understanding of consumer behavior in the MBG program. The high model performance, with an accuracy of 89.3%, indicates that behavioral variables such as awareness, trust, and accessibility play a dominant role in predicting program acceptance. This aligns with modern marketing theory, which emphasizes that perceptual and trust-related factors have a stronger influence on decision-making compared to purely demographic attributes.

The segmentation analysis identifies three distinct consumer groups with different behavioral characteristics, where the medium-acceptance segment emerges as the most strategic target for marketing intervention. This supports the effectiveness of the segmentation, targeting, and positioning (STP) framework in designing more focused and impactful communication strategies. In addition, the normalized confusion matrix confirms that the model achieves strong classification performance across most classes, although some misclassification is observed in segments with overlapping characteristics. This suggests that further improvement in feature representation or the inclusion of additional variables may enhance model discrimination. Furthermore, the sentiment analysis results for 2025 reveal a dominant positive perception of the MBG program, with a consistent upward trend over time. This indicates that current communication efforts are beginning to generate meaningful impact on public acceptance. However, the presence of neutral and negative sentiments highlights the need for more targeted and adaptive communication strategies, particularly in improving awareness and trust among specific groups.

From a practical perspective, the integration of predictive modeling, segmentation, and behavioral analysis enables more precise and data-driven marketing decisions. Targeted strategies focusing on key variables such as awareness and trust are shown to increase engagement by approximately 15–20%, reaching up to 18.6% in certain segments. This demonstrates that AI-driven approaches not only enhance analytical accuracy but also provide tangible benefits in improving program effectiveness. Overall, this study contributes to bridging the gap between marketing management and computer science by proposing a data-driven and explainable framework for public program optimization. Compared to previous studies relying on conventional statistical approaches with accuracy levels around 70–80%, the proposed model achieves superior performance and deeper behavioral insights. Therefore, the integration of AI, segmentation, and explainability represents a significant advancement in developing adaptive and evidence-based marketing strategies for large-scale public programs such as MBG

4. CONCLUSION

Artificial Intelligence and marketing analytics provides an effective approach for understanding and improving public acceptance of the MBG program. The proposed data-driven framework successfully identifies key behavioral factors influencing participation, with awareness, trust, and accessibility emerging as the most significant determinants. The predictive model achieves strong performance, with an accuracy of 89.3%, indicating its capability to reliably estimate program acceptance. The segmentation analysis further reveals distinct consumer groups, enabling more precise targeting and positioning strategies. In addition, sentiment analysis confirms a dominant and increasing positive perception of the program in 2025, indicating that current communication efforts are beginning to yield meaningful results. The combination of predictive modeling, segmentation, and sentiment analysis provides actionable insights that support more effective and targeted marketing strategies. From a practical perspective, the findings highlight that AI-driven marketing strategies can significantly enhance engagement, with improvements of up to 18.6% in targeted segments. This confirms that data-driven approaches are not only analytically robust but also impactful in real-world implementation. Overall, this research contributes to bridging the gap between marketing management and computer science by introducing an integrated, explainable, and adaptive framework for public program optimization. Future research is recommended to incorporate real-time data, social media analytics, and more advanced deep learning models to further improve predictive accuracy and strategic effectiveness in large-scale public initiatives

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BIOGRAPHIES OF AUTHORS
