

# Analysis of Students' Perceptions of the Free Nutritious Food Program (MBG) Based on K-Means Clustering

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## ABSTRACT

The Free Nutritious Food Program is a strategic policy to support students' nutritional resilience and readiness to learn. This study examined students' perceptions of the program and identified respondent profiles using the K-Means clustering algorithm. Data from 501 students were collected through a Likert-scale questionnaire and analyzed to determine distinct perception patterns. The results revealed five clusters with strong validity, indicated by a silhouette value of 0.917. Overall, 74.6% of respondents expressed positive perceptions, suggesting that the program has been well received and supports school nutrition. However, some groups reported concerns regarding menu variety and cleanliness at distribution points. These findings underscore the need for routine quality monitoring, standardized implementation procedures, and greater attention to service consistency. Future studies should also include objective indicators such as body mass index and school attendance to provide a more comprehensive evaluation of program impact.

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## 1. INTRODUCTION

Achieving the Golden Indonesia 2045 vision depends on strengthening human capital starting in primary education. Persistent nutrition problems such as stunting and undernutrition continue to undermine children's cognitive development, learning capacity, and academic performance [1], [2], [3]. To bolster nutritional resilience and improve students' readiness to learn, the Indonesian government introduced the Free Nutritious Meals (MBG) program as a school-based nutrition intervention [4], [5], [6]. Recent studies indicate that school feeding programs can improve attendance, learning outcomes, and nutritional status, but their effects depend on implementation quality and beneficiary acceptance [3], [7]. Additionally, concerns about energy balance and sustainability underscore the need to assess school meal interventions beyond distribution coverage alone [8], [9].

Evaluating MBG solely by distribution volume risks overlooking key dimensions such as students' perceptions of taste, menu variety, cleanliness, service quality, and overall satisfaction factors linked to participation, adherence, and food waste [10], [11], [12], [13]. The indicators in this study were chosen based on prior school-meal perception research and food-service evaluation literature, which highlight healthfulness, accessibility, participation, food safety, and user experience as core assessment dimensions [10], [12], [13], [14]. Indonesia's geographic diversity and decentralized governance also produce variation in implementation, including differences in local ingredient availability, fortification standards, and food safety practices; thus, evaluations should account for local context and regional heterogeneity [14], [15].

To address these gaps, this study applies Educational Data Mining (EDM) with the K-Means algorithm to map students' perception patterns of MBG implementation. EDM and clustering techniques have been widely used in educational assessment, dietary pattern analysis, and student grouping studies [16], [17],

[18], [19], while K-Means remains a well-established method for pattern discovery and profile classification [20]. Previous studies in Indonesia also demonstrate the usefulness of K-Means for classifying educational quality and student-related characteristics [21], [22]. The study aims to: (1) chart variation in student perceptions of MBG menu and service quality; (2) identify clusters of students with differing acceptance levels; and (3) develop evidence-based operational policy recommendations. Practically, the work provides quantitative support for menu standardization, routine quality audits, and distribution improvements; theoretically, it extends the application of EDM and clustering to public policy evaluation across diverse geographic and cultural settings. The findings are intended to help local policymakers design more targeted, equitable, and sustainable interventions.

## 2. RESEARCH METHOD

This study employs a descriptive quantitative approach with a cross-sectional design to assess students' perceptions of the Free Nutritious Food Program (MBG). The methodological foundation is Educational Data Mining (EDM), commonly used to uncover meaningful patterns in educational and behavioral data through clustering and classification techniques [16], [20]. Prior research has effectively applied K-Means to educational evaluation and dietary pattern analysis [17], [18], [19], and to grouping student-related characteristics in Indonesian contexts [21], [22]. However, many of these studies emphasize classification outcomes over perception-based evaluation and often provide limited explanation of indicator validation and cluster interpretation. To address this gap, the present study combines survey-based measurement with clustering analysis to deliver a more transparent and reproducible evaluation of MBG implementation. Data analysis used the K-Means clustering algorithm to group respondents based on similarities in their responses. The study workflow was organized systematically from initial to final stages (Figure 1).

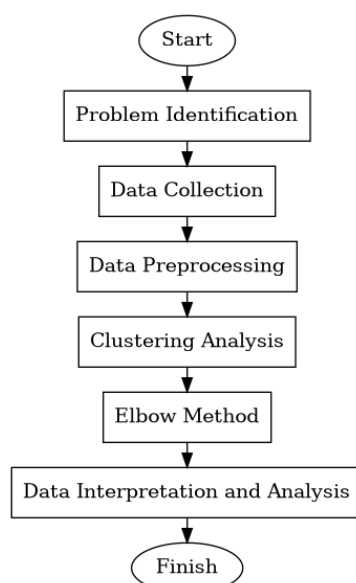


Figure 1. Research Flow

### 2.1. Problem Identification and Data Collection

This research aims to provide an in-depth evaluation of students' perceptions regarding the implementation of MBG in the Manokwari area. The sample was selected purposively and comprised 501 active beneficiary respondents from junior high schools (SMPN 6, SMP Yapis, SMPN 1 and 2 Manokwari) and senior high school/vocational/Islamic high school levels (MAN Manokwari, SMA Yapis, SMAN 1, SMKN 1 and 2 Manokwari), including satellite areas such as Prafi. The sampling approach was chosen to ensure that respondents were direct beneficiaries of the program and able to provide relevant evaluations of its implementation.

Primary data were collected over approximately two months (3 November 2025–23 January 2026) using a digital Likert-scale questionnaire (1–5). The instrument measured five dimensions: food quality, menu variety, timeliness of distribution, impact on learning readiness, and overall satisfaction. These indicators were derived from prior school meal perception studies and food-service evaluation literature, which emphasize food acceptability, service quality, participation, and user experience as essential dimensions of school feeding assessment [10], [12], [13], [14]. The instrument was validated through expert review to confirm content

relevance and was tested for internal consistency using Cronbach's Alpha. The analysis also considered potential differences in perceptions related to socio-economic background, as suggested in prior educational grouping studies [23].

## 2.2. Data Preprocessing

After data collection, preprocessing was performed to ensure data quality before the core analysis. Raw data from Google Forms were processed using Microsoft Excel through cleaning procedures that included removing duplicate responses and checking for completeness to minimize missing data. The cleaned dataset was then converted into CSV format for compatibility with the Orange Data Mining software. Next, the data were standardized using the Z-score method to place all variables on a comparable scale. This is necessary because K-Means is sensitive to variable magnitude and can be biased when indicators have different ranges. The standardized score for each value  $x$  was calculated as in Equation 1.

$$Z = \frac{x - \mu}{\sigma} \quad (1)$$

where  $x$  is the original value,  $\mu$  is the mean of the variable, and  $\sigma$  is the standard deviation.

This step ensures that each indicator contributes equally to the clustering process and supports more stable and interpretable cluster formation [16], [20], [21].

## 2.3 K-Means Clustering Analysis

The core data processing in this study used Orange Data Mining software to implement the K-Means algorithm. K-Means is an unsupervised clustering method that partitions data into  $k$  groups by minimizing the distance between observations and their assigned cluster centroids [16], [20]. The algorithm is based on two core principles: minimizing within-cluster variance and maximizing between-cluster separation.

The Euclidean distance between respondent  $x_i$  and centroid  $c_j$  was computed as Equation 2.

$$d(x_i, c_j) = \sqrt{\sum_{p=1}^m (x_{ip} - c_{jp})^2} \quad (2)$$

where  $m$  is the number of variables,  $x_{ip}$  is the value of the variable  $p$  for respondent  $i$ , and  $c_{jp}$  is the centroid value for the cluster  $j$ . Each respondent was assigned to the cluster with the minimum distance, as determined by Equation 3.

$$\text{Cluster}(x_i) = \arg \min_j d(x_i, c_j) \quad (3)$$

After the assignment, the centroid of each cluster was updated using the mean of all members in that cluster, as shown in Equation 4.

$$c_j = \frac{1}{n_j} \sum_{i=1}^{n_j} x_i \quad (4)$$

where  $n_j$  is the number of observations in the cluster  $j$ .

These two steps were repeated iteratively until the centroid values no longer changed or the algorithm reached convergence. The objective function minimized by K-Means is the Sum of Squared Errors (SSE), which can be seen in Equation 5.

$$\text{SSE} = \sum_{j=1}^k \sum_{x_i \in C_j} \|x_i - c_j\|^2 \quad (5)$$

This formulation ensures that the final clusters are internally compact and externally distinct [24], [25].

## 2.4. Determination of the Optimal Number of Clusters (Elbow Method)

Before running the final clustering, the optimal number of clusters ( $k$ ) was determined using the Elbow Method. This technique evaluates the SSE for several values of  $k$  and identifies the point at which the

decrease in SSE begins to slow substantially. That point is considered the “elbow” and represents a balance between model simplicity and cluster quality [17], [18]. In this study, multiple cluster numbers were tested, and the SSE trend was observed to determine the most appropriate k. The chosen number of clusters was then used in the final K-Means analysis to produce a stable and meaningful grouping structure that reflects students’ perception patterns. This validation step improves methodological transparency and supports reproducibility.

**2.5. Data Interpretation and Analysis**

After clustering, the next stage involved interpreting the distinctive characteristics of each cluster based on centroid values. In this phase, researchers assigned substantive labels to each group, such as High, Moderate, or Low Perception, depending on the relative pattern of responses across the five indicators. Cluster interpretation was guided by the centroid profile of each group and by comparing the dominance of positive or negative values across indicators [26]. To strengthen validation, the quality of the clustering solution was assessed using internal evaluation via silhouette analysis, which measures how well each observation fits within its own cluster relative to other clusters. The silhouette coefficient ranges from -1 to 1, with values closer to 1 indicating stronger cluster separation and cohesion. This approach is appropriate for validating K-Means results and supports the interpretability of cluster structure. The final analysis focused on identifying the indicators most influential in shaping student satisfaction or dissatisfaction with MBG implementation. The interpretation results were then translated into strategic conclusions for program improvement.

**2.6. Conclusions and Recommendations**

After the entire data processing sequence was completed, the study drew conclusions from the cluster analysis results to assess the extent to which the MBG Program’s effectiveness had been achieved in the field. These conclusions not only present an overall picture of program acceptance but also serve as the primary basis for formulating evaluative recommendations for organizers. Through these recommendations, it is expected that strategic steps will be taken for continuous improvement, particularly to enhance service quality standards, strengthen menu consistency, and improve the accuracy of food distribution mechanisms in each target school. The recommendations also align with prior findings that school meal programs are most effective when implementation quality, acceptability, and safety are maintained consistently [10], [12], [13], [14], [27]

**3. RESULTS AND ANALYSIS**

**3.1. Data Collection**

The preliminary phase of the study involved collecting primary data by distributing digital questionnaires to junior and senior high school students in Manokwari. A total of 501 valid responses were obtained. The survey instrument used a 1–5 Likert scale to assess students’ perceptions of the Free Nutritious Meal Program (MBG), with the following weights: 1 = Very Dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, and 5 = Very Satisfied. Table 1 presents the raw questionnaire data in Excel.

**Table 1. Questionnaire Data Results**

No	Timestamp	Name	Gender	School	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	.....	Q23
1	2025-11-03 15:41:07	Annisa	Female	State Vocational High School 1 Manokwari	5	5	5	5	5	5	5	5	5	5	.....	5
2	2025-11-03 15:50:25	Abigail	Female	State Senior High School 1 Manokwari	5	4	4	3	3	4	4	3	4	4	.....	5
3	2025-11-03 15:50:41	Awa	Female	State Senior High School 1 Manokwari	5	5	5	5	5	5	5	5	5	5	.....	5
4	2025-11-03 15:51:36	Annisa Salsa	Female	State Senior High School 1 Manokwari	5	5	3	4	5	5	5	5	5	5	.....	5
5	2025-11-03 15:52:51	Gita	Female	State Vocational High School 1 Manokwari	5	5	5	5	5	5	4	3	4	4	.....	5
6	2025-11-03 16:01:24	Putri Kirana	Female	State Vocational High School 1 Manokwari	5	3	4	3	5	4	5	3	4	3	.....	5
7	2025-11-03 16:15:16	Alghazali	Female	State Vocational High School 1 Manokwari	5	5	5	5	5	5	5	5	5	5	.....	5
8	2025-11-03 16:21:38	Alysia Sekar	Male	State Senior High School 1 Manokwari	4	4	4	4	4	3	4	5	3	3	.....	4

No	Timestamp	Name	Gender	School	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	.....	Q23
9	2025-11-03 16:23:43	Muhammad Rifat	Female	State Senior High School 1 Manokwari	1	3	4	2	2	4	5	4	5	4	.....	4
10	2025-11-03 17:40:14	Ghulamazan Zakiya	Male	YAPIS Junior High School Manokwari	1	2	1	1	4	2	2	3	1	2	.....	2
.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
501	2026-01-23 20:23:40	Nisa	Female	State Senior High School 1 Manokwari	4	4	4	4	4	4	4	4	4	4	.....	4

The questionnaire comprised 23 statements that served as clustering attributes and were grouped into five perception dimensions. These dimensions were developed to reflect prior school-meal evaluation studies emphasizing awareness, accessibility, service quality, food quality, trust, satisfaction, and program impact [10], [12], [13], [14]. The first dimension concerns awareness and access to information, evaluating how well students understand the program's criteria and schedule (items 1–4). The second dimension examines service quality and accessibility, assessing convenience of location, efficiency of distribution, and staff friendliness (items 5–8 and 15). Product quality is evaluated through indicators of suitability for consumption, hygiene standards, portion adequacy, and menu variety (items 9–12). The fourth dimension analyzes trust and transparency, including consistency of schedules, management openness, and fairness in food distribution (items 13–14 and 16–18). Finally, the satisfaction and impact dimension gauges overall satisfaction, economic benefits for families, and respondents' support for the program's long-term sustainability (items 19–23). All items are detailed in Table 2.

**Table 2.** Questionnaire Instrument on Student Perceptions of the MBG Program

No	Questionnaire Statement
1	I am aware that there is a free meal program at school.
2	I understand the requirements to receive free meals.
3	Information about the schedule and distribution locations is readily available.
4	The program has been clearly socialized by the government/related institutions.
5	The food distribution locations are easily accessible.
6	The process of obtaining free meals is not complicated.
7	The distribution time is suitable for students' needs.
8	The service staff are friendly and helpful.
9	The food provided is fit for consumption.
10	The food received meets hygiene standards.
11	The portion size is sufficient for recipients.
12	The variety of food makes the program appealing.
13	I frequently utilize this free meal program.
14	The program is available regularly according to schedule.
15	There are no difficulties in accessing this program.
16	I believe the program is managed transparently.
17	There is no favoritism in the distribution of food.
18	The government or implementing agency can be trusted to maintain fairness in the program.
19	I am satisfied with the implementation of this free meal program.
20	This program helps reduce my family's economic burden.
21	I would support continuing this program in the future.
22	I would recommend this program to others.
23	This program aligns with the goal of improving community welfare.

After verifying completeness and removing duplicate entries for 501 respondents in Excel, the data were exported to CSV format. The representative sample in Figure 2 and Table 1 was subsequently imported into the Orange Data Mining software for analysis.

### 3.2. Data Pre-processing and Standardization

The initial dataset comprised 501 student respondents from middle and high school levels. Prior to clustering, a critical preprocessing step was applied: column normalization. This normalization aimed to harmonize the scales of the variables, since K-Means is a distance-based algorithm and variables with larger ranges could unduly influence the clustering results. An example of the standardized data is shown in Table 3. The sample data come from records 1 through 7 and 501. The values reflect a transformation of each indicator to a 1–5 scale, where 1 denotes the lowest level for that indicator and 5 denotes the highest.

**Table 3.** Sample Standardized Data

Row	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5	Indicator 6	Indicator 7	---	Indicator 23
1	1	1	1	1	1	1	1	---	1
2	1	0.75	0.75	0.5	0.5	0.75	0.75	---	1
3	1	1	1	1	1	1	1	---	1
4	1	1	0.5	0.75	1	1	1	---	1
5	1	1	1	1	1	1	0.75	---	1
6	1	0.5	0.75	0.5	1	0.75	1	---	1
7	1	1	1	1	1	1	1	---	1
---	---	---	---	---	---	---	---	---	---
501	0.75	0.75	0.75	0.75	0.75	0.75	---	1	0.75

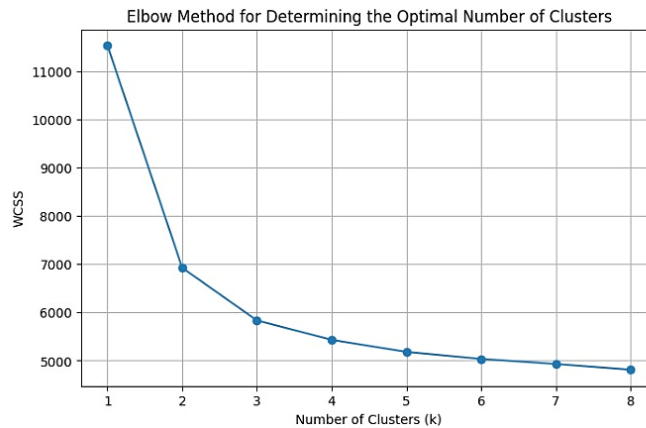
This table shows that all respondents rated the program positively with high scores, indicating support for and confidence in the free meal program. This normalization helps the algorithm cluster respondents based on variables that have been scaled equally, making the analysis process more accurate and objective.

**3.3 Determination of Optimal Number of Clusters (Elbow Method)**

The optimal number of clusters was determined using the Elbow Method by computing the Sum of Squared Errors (SSE). The ideal value of k corresponds to the "elbow" point on the SSE plot, where adding additional clusters no longer yields a meaningful reduction in SSE [21]. A comparative analysis of SSE values to identify the most representative number of clusters from k=2 to k=12 is presented in Table 4 and Figure 2.

**Table 4.** Comparison of SSE Values for Various Numbers of Clusters (k=2 to k=12)

Experiment	Number of Clusters (k)	SSE Value
1	2	6922.76
2	3	5833.43
3	4	5446.03
4	5	5183.57
5	6	5104.49
6	7	4983.35
7	8	4812.94
8	9	4725.12
9	10	4650.33
10	11	4580.88
11	12	4520.45



**Figure 2.** Elbow Method Plot

The optimal number of clusters was determined by evaluating the SSE values across eleven experimental iterations (k=2 to k=12) as detailed in Table 4 and Figure 2. The Elbow Method reveals a distinct inflection point at k=5, where the previously sharp decline in the Within-Cluster Sum of Squares (WCSS) begins to plateau. Beyond this threshold, the reduction in SSE becomes marginal, varying only by 79 to 170 points, indicating that additional clusters do not meaningfully enhance data compactness. This selection is further validated by a high average Silhouette Score of 0.917, confirming that k=5 provides the most stable and cohesive classification for the 501 respondents, establishing a reliable basis for subsequent profiling [4].

### 3.4 Visualization (Scatter Plot and Silhouette Plot)

After running the K-Means algorithm with  $k = 5$ , the data distribution and clustering strength are visualized using a Scatter Plot and a Silhouette Plot. Figure 3 (Scatter Plot) and Figure 4 (Silhouette Plot).

The visualization in Figure 3 maps the clustering strength based on the silhouette values for each group. The primary data concentration, which falls within the coefficient range of 0.60 to 0.76, indicates that the model has reached optimal convergence. The density of points in C1 and C2 suggests highly similar response patterns among the members of these groups. Meanwhile, C5 stands out with the most significant structural advantage, with values approaching 0.76. Although there are variations in perception within C3 and C4 (ranging from 0.62 to 0.66), the model's validity remains intact as both clusters are distinctly separated from the others.

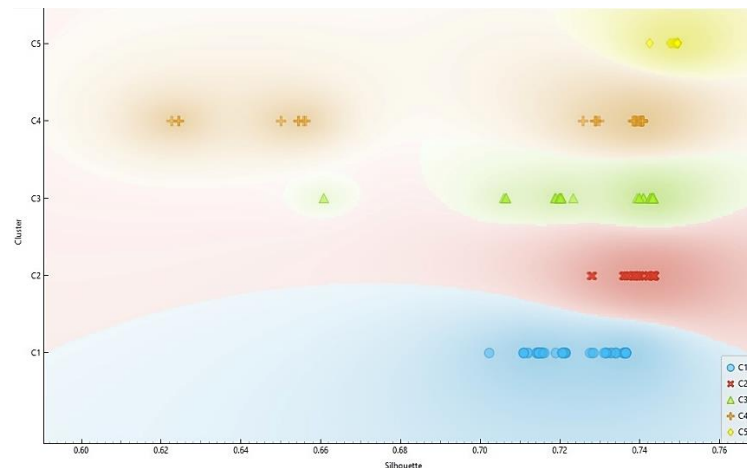


Figure 3. Scatter Plot

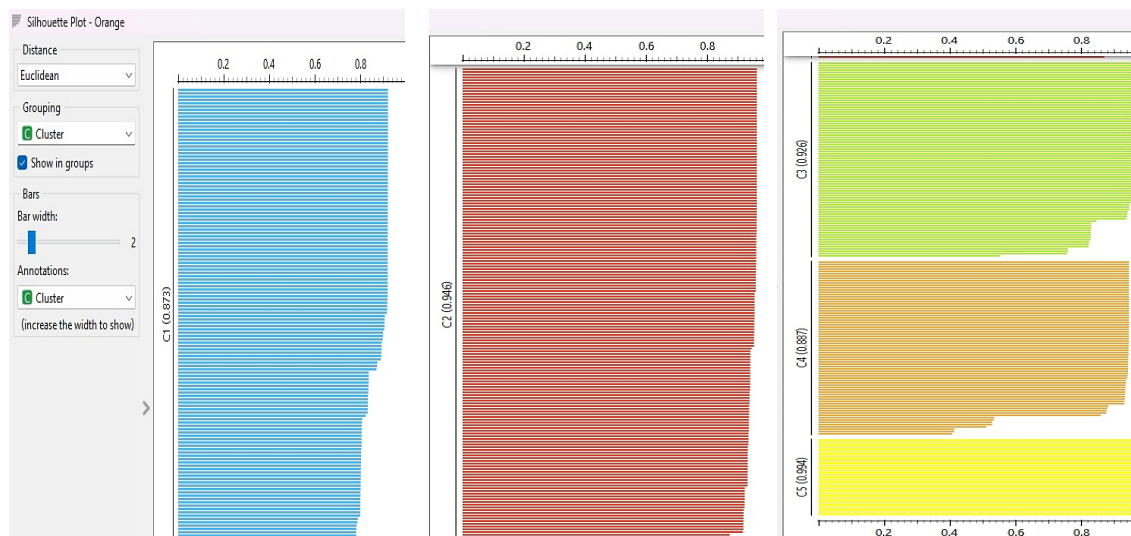


Figure 4. Silhouette Plot

The quality of data partitioning in this study was further evaluated through the silhouette coefficient analysis shown in Figure 4, which reveals a very high level of cohesion across all groups (C1–C5). Cluster 1 (C1) recorded a value of 0.873, reflecting a robust group structure despite encompassing somewhat heterogeneous positive perceptions. Cluster 2 (C2), the largest segment with 173 respondents, achieved a high coefficient of 0.946. This demonstrates the algorithm's success in grouping respondents with extreme ratings into consistent behavioral patterns. Clustering stability is also evident in Cluster 3 (C3) with a value of 0.926 and Cluster 4 (C4) at 0.887, representing groups with stable satisfaction and satisfied respondents who tend to be more critical, respectively. Cluster 5 (C5) achieved the highest validity, with a score of 0.994, indicating near-perfect perceptual homogeneity. Collectively, silhouette values significantly exceeding the 0.5 threshold and the absence of negative values confirm that the  $k = 5$  configuration possesses superior structural integrity and serves as a highly reliable foundation for strategic decision-making.

Based on the visualizations and coefficient analyses above, the specific characteristics of each cluster are summarized in Table 5.

**Table 5.** Summary of Cluster Characteristics (C1–C5)

Cluster	Key Characteristics	Meaning
C1	Puas stabil	Good and consistent implementation
C2	Ekstrem	Uneven quality (key finding)
C3	Netral-puas	Further quality improvement required
C4	Kurang puas	Presence of operational issues
C5	Sangat puas	Ideal example of implementation

### 3.5. Cluster Interpretation and Analysis

The clustering results for 501 respondents produced a frequency distribution of perceptions divided into five distinct cluster profiles, as shown in Table 6 below:

**Table 6.** Student Perception Cluster Recapitulation Results

Attribute	Very Satisfied	Satisfied	Neutral	Dissatisfied	Very Dissatisfied	Total Respondents
Cluster 1	44	44	24	16	7	135
Cluster 2	80	66	2	0	25	173
Cluster 3	30	33	13	5	3	84
Cluster 4	29	26	11	9	0	75
Cluster 5	6	16	11	0	0	33
Total	189	185	61	30	35	501

The data in Table 6 show that the majority of respondents (74.6% or 374 students) gave positive responses, confirming the overall success of the MBG Program in Manokwari. The neutral group comprised 12.2% of respondents, while the remaining 13.2% expressed dissatisfaction. Specifically, Cluster 2 shows a sharp disparity: although it has the highest number of "Very Satisfied" respondents, it also includes 25 "Very Dissatisfied" respondents. This phenomenon indicates an anomaly or a quality gap in service at certain distribution points that requires further standardization so that the program quality is consistent for all students.

### 3.6. Discussion and Analysis

The findings show that students in Manokwari generally responded positively to the MBG program, with 74.6% of respondents falling into the satisfied category. This indicates that the program has been well-received as a school-based nutrition intervention and is perceived as supporting students' daily learning. The five clustering attributes, information access, service accessibility, food quality, trust/transparency, and satisfaction/impact, capture the main dimensions shaping students' judgments of the program. This aligns with previous school meal studies showing that acceptance is influenced not only by food availability but also by service experience, perceived healthfulness, and implementation quality [10], [12], [13], [14]. The K-means analysis produced five robust clusters with a Silhouette value of 0.917, indicating student perception patterns are well separated and internally coherent. Cluster C1 represents students with consistently positive perceptions, suggesting the program functions effectively in some schools and distribution points. Cluster C2 is the largest group and shows the most polarized responses, containing both very satisfied and very dissatisfied students. This suggests uneven service quality, with some students receiving good service while others experience problems with menu consistency, hygiene, or distribution. Cluster C3 reflects moderately positive perceptions but still indicates room for improvement. Cluster C4 represents students with lower satisfaction and likely operational issues. Cluster C5 reflects the strongest acceptance of the program and may serve as a benchmark for effective implementation.

These cluster differences are important because they show that MBG is not experienced uniformly across all respondents. Although the program is broadly successful, the existence of mixed and dissatisfied clusters suggests that implementation standards still vary between schools or service points. From a policy perspective, this means program evaluation should not stop at distribution coverage. Instead, it should also monitor menu variety, cleanliness, timeliness, and fairness in service delivery. The findings support the need for standard operating procedures, periodic quality audits, and more consistent supervision across locations, especially in regions with geographic and logistical challenges. This is also consistent with earlier studies emphasizing that school meal programs are most effective when implementation quality, food safety, and beneficiary acceptance are maintained consistently [14], [15]. Methodologically, this study confirms the usefulness of K-Means clustering in educational and public policy evaluation. The results align with prior work showing that clustering can reveal hidden respondent profiles and support clearer interpretation of perception-based data [16], [20], [21], [22]. The advantage of this approach is that it not only reports average satisfaction but also identifies subgroups with different experiences. However, the study has limitations. First, the analysis is based on self-

reported Likert-scale data, which may be subject to bias. Second, the study focuses only on Manokwari, so the results cannot be generalized to all regions. Third, the evaluation does not include objective health indicators such as BMI, attendance, or academic performance. Future studies should address these limitations by combining perception data with objective indicators and by testing alternative clustering techniques to obtain a more robust grouping structure.

#### 4. CONCLUSION

This study shows that the MBG program in Manokwari was generally well received by students, with most respondents expressing positive perceptions of it. K-Means clustering identified five distinct perception groups, confirming that while the program is broadly accepted, its implementation is not yet uniform across all schools and distribution points. The main issue is the presence of mixed and dissatisfied clusters, indicating that students experience varying levels of service quality, food consistency, and fairness in distribution. These findings suggest that MBG has strong potential as a school-based nutrition intervention, but its effectiveness depends on more consistent implementation. To improve performance, local policymakers and organizers should strengthen operational standards, regularly monitor food quality and hygiene, and ensure that distribution procedures are fair and timely across all locations. The cluster results can serve as a practical basis for targeting schools or areas that need closer supervision and service improvement. For future research, it is recommended to use alternative clustering methods, compare results across wider geographic areas, and combine perception data with objective indicators such as nutritional status, attendance, and academic performance. Future studies may also explore students' textual feedback to better understand their experiences in greater depth. Overall, this study provides useful evidence for improving the MBG program so its benefits can be delivered more evenly, effectively, and sustainably.

#### REFERENCES

- [1] C. Wall, T. Tolar-Peterson, N. Reeder, M. Roberts, A. Reynolds, and G. Rico Mendez, "The Impact of School Meal Programs on Educational Outcomes in African Schoolchildren: A Systematic Review," *Int. J. Environ. Res. Public Health*, vol. 19, no. 6, p. 3666, Mar. 2022, doi: 10.3390/ijerph19063666.
- [2] K. Hussein, T. C. Mekonnen, F. M. Hussien, T. D. Alene, and M. S. Abebe, "School Feeding and Nutritional Status of Students in Dubti District, Afar, Northeast Ethiopia: Comparative Cross-Sectional Study," *Pediatric Health Med. Ther.*, vol. Volume 14, pp. 217–230, Jun. 2023, doi: 10.2147/PHMT.S412740.
- [3] B. Mohammed, T. Belachew, S. Kedir, and K. H. Abate, "Effect of school feeding program on academic performance of primary school adolescents: A prospective cohort study," *Clin. Nutr. ESPEN*, vol. 56, pp. 187–192, Aug. 2023, doi: 10.1016/j.clnesp.2023.05.017.
- [4] L. Wahyuniar and E. N. Iman Pustakasari, "Effectiveness of the Free Nutritious Meal (MBG) Program on Nutritional Status, Learning Concentration, and Student Attendance in South Jakarta Elementary Schools," *Jurnal Medisci*, vol. 3, no. 3, pp. 201–221, Dec. 2025, doi: 10.62885/medisci.v3i3.973.
- [5] I. L. Pramesthi et al., "Evaluating the Impact of Indonesia's National School Feeding Program (ProGAS) on Children's Nutrition and Learning Environment: A Mixed-Methods Approach," *Nutrients*, vol. 17, no. 22, p. 3575, Nov. 2025, doi: 10.3390/nu17223575.
- [6] Y. F. Kasi, M. E. Ga'a, T. B. Jajuri, and D. V. Bai, "Perceptions of Teachers on the Free Nutritious Meal Program Implementation in Indonesia: Benefits and Challenges," *Pedagonal: Jurnal Ilmiah Pendidikan*, vol. 9, no. 2, pp. 180–187, Oct. 2025, doi: 10.55215/pedagonal.v9i2.54.
- [7] B. Barnabas, M. Bavorova, and M. Y. Madaki, "The Effect of School Feeding Program on Pupils' Enrolment, Attendance and Performance in Northeastern Region of Nigeria," *Sage Open*, vol. 14, no. 4, Oct. 2024, doi: 10.1177/21582440241255809.
- [8] W. Stroebe, "Is the energy balance explanation of the obesity epidemic wrong?," *Appetite*, vol. 188, p. 106614, Sep. 2023, doi: 10.1016/j.appet.2023.106614.
- [9] M. Springmann, M. P. Hansoge, L. Schultz, S. Pastorino, and D. A. P. Bundy, "The health, environmental, and cost implications of providing healthy and sustainable school meals for every child by 2030: a global modelling study," *Lancet Planet. Health*, vol. 9, no. 11, p. 101278, Nov. 2025, doi: 10.1016/j.lanplh.2025.06.002.
- [10] M. Tsai, L. D. Ritchie, P. Ohri-Vachaspati, and L. E. Au, "Student Perception of Healthfulness, School Lunch Healthfulness, and Participation in School Lunch: The Healthy Communities Study," *J. Nutr. Educ. Behav.*, vol. 51, no. 5, pp. 623–628, May 2019, doi: 10.1016/j.jneb.2019.01.014.
- [11] K. C. Fiedler et al., "A Qualitative Exploration of Parent and School Staff Perceptions of Freshly Prepared Meals and Food Waste Implications in California Elementary Schools," *J. Nutr. Educ. Behav.*, vol. 57, no. 11, pp. 1048–1059, Nov. 2025, doi: 10.1016/j.jneb.2025.07.006.
- [12] D. Orta-Aleman et al., "Students' Perspectives on the Benefits and Challenges of Universal School Meals Related to Food Accessibility, Stigma, Participation, and Waste," *J. Nutr. Educ. Behav.*, vol. 56, no. 9, pp. 599–610, Sep. 2024, doi: 10.1016/j.jneb.2024.04.011.
- [13] M. D. Zuercher et al., "Parent perceptions of school meals and how perceptions differ by race and ethnicity," *Health Affairs Scholar*, vol. 2, no. 1, Jan. 2024, doi: 10.1093/haschl/qxad092.

- [14] A. P. Muraro et al., "Association of school meals and eating behavior, diet quality, food safety, and BMI among Brazilian students: a systematic review," *Cien. Saude Colet.*, vol. 30, no. 5, May 2025, doi: 10.1590/1413-81232025305.14892023.
- [15] N. P. W. P. Sari, A. Mazenda, C. L. F. Katiyatiya, M.-H. Nguyen, and Q.-H. Vuong, "Policy analysis in school meals program: regulation impacts on in-school food fortification," *J. Hunger Environ. Nutr.*, vol. 20, no. 6, pp. 1024–1041, Nov. 2025, doi: 10.1080/19320248.2025.2505041.
- [16] R. Liu, "Data Analysis of Educational Evaluation Using K-Means Clustering Method," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–10, Jul. 2022, doi: 10.1155/2022/3762431.
- [17] C. O'Hara, A. O'Sullivan, and E. R. Gibney, "A Clustering Approach to Meal-Based Analysis of Dietary Intakes Applied to Population and Individual Data," *J. Nutr.*, vol. 152, no. 10, pp. 2297–2308, Oct. 2022, doi: 10.1093/jn/nxac151.
- [18] J. F. López-Gil and M. F. Martínez-López, "Clustering of Dietary Patterns Associated with Health-Related Quality of Life in Spanish Children and Adolescents," *Nutrients*, vol. 16, no. 14, p. 2308, Jul. 2024, doi: 10.3390/nu16142308.
- [19] F. Nurulhikmah and D. N. E. Abdi, "Classification of Foods Based on Nutritional Content Using K-Means and DBSCAN Clustering Methods," *Teknika*, vol. 13, no. 3, pp. 481–486, Oct. 2024, doi: 10.34148/teknika.v13i3.1067.
- [20] A. M. Ikotun, A. E. Ezugwu, L. Abualigah, B. Abuhaija, and J. Heming, "K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data," *Inf. Sci. (N. Y.)*, vol. 622, pp. 178–210, Apr. 2023, doi: 10.1016/j.ins.2022.11.139.
- [21] Z. Mustakim and R. Kamal, "K-means clustering for classifying the quality management of secondary education in Indonesia," *Jurnal Cakrawala Pendidikan*, vol. 40, no. 3, pp. 725–737, Oct. 2021, doi: 10.21831/cp.v40i3.40150.
- [22] H. L. Siregar, R. Hidayanthi, and A. L. D. Sakti, "Implementation of K-Means clustering on student learning achievements based on social economic and social related," *Research and Development in Education (RaDeN)*, vol. 4, no. 2, pp. 1447–1459, Dec. 2024, doi: 10.22219/raden.v4i2.36742.
- [23] C. A. Orihuela, R. Evans, and S. Mrug, "Student Stakeholders' Perspectives on Middle School Lunch Programs: A Qualitative Study," *Am. J. Health Educ.*, vol. 55, no. 4, pp. 287–297, Jul. 2024, doi: 10.1080/19325037.2023.2297286.
- [24] X. Hou, T. Xu, and C. Zhang, "Building Consensus with Enhanced K-means++ Clustering: A Group Consensus Method Based on Minority Opinion Handling and Decision Indicator Set-Guided Opinion Divergence Degrees," *Electronics (Switzerland)*, vol. 14, no. 8, Apr. 2025, doi: 10.3390/electronics14081638.
- [25] I. Herdiana, M. A. Kamal, Triyani, M. N. Estri, and Renny, "A More Precise Elbow Method for Optimum K-means Clustering," Feb. 2025, [Online]. Available: <http://arxiv.org/abs/2502.00851>
- [26] J. Lim and J. Oh, "Cluster-Based Evaluation of Dietary Guideline Adherence and Food Literacy Among Adolescents: Implications for Tailored Diets," *Nutrients*, vol. 18, no. 2, p. 241, Jan. 2026, doi: 10.3390/nu18020241.
- [27] P. Badyal and T. Moffat, "Considerations for diverse, equitable, and inclusive school food programs in the USA and Canada," *Health Promot. Int.*, vol. 40, no. 2, Mar. 2025, doi: 10.1093/heapro/daaf015.

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