Segmentation of Public Perceptions of Integrity Zones Using the K-Means Algorithm and Agglomerative Clustering

Sigit Prabowo, Muhammad Iqbal

Abstract

The development of Integrity Zones toward Corruption-Free Zones (WBK) and Clean and Service-Oriented Bureaucracy Zones (WBBM) is part of bureaucratic reform efforts to achieve public services that are clean, accountable, and focused on public satisfaction. Public perception of the implementation of Integrity Zones is a key indicator in evaluating the quality of services provided by government agencies. However, survey results are generally analyzed descriptively, making it difficult to identify the characteristics of specific community groups based on their perception patterns. This study aims to segment public perceptions of Integrity Zones using the K-Means and Agglomerative Clustering algorithms. The research data were derived from the 2025 Survey on the Assessment of Integrity Zone Development Toward WBK/WBBM at the Medan Health Quarantine Center, involving 1,046 respondents. The survey included the Anti-Corruption Perception Index (IPAK), consisting of five indicators, and the Service Quality Perception Index (IPKP), consisting of eight indicators. The research stages included data cleaning, variable transformation and normalization, determining the optimal number of clusters, the clustering process, and evaluating cluster quality using the Silhouette Score and dendrogram visualization. The research results are expected to identify the characteristics of each public perception group so that they can serve as considerations for improving service quality and strengthening the implementation of the Integrity Zone within the Medan Health Quarantine Center.

***Keywords**: Integrity Zone, Service Quality Perception Index, Anti-Corruption Perception Index, K-Means Clustering, Agglomerative Clustering.*

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Introduction

The development of the Integrity Zone (ZI) is part of bureaucratic reform aimed at strengthening governance, preventing corruption, and improving the quality of public services. Several studies on the ZI indicate that internal reforms must go hand in hand with improvements in the quality of services as perceived by the public. In the context of health services, for example, bureaucratic reform is linked to efforts to maintain service quality while strengthening internal organizational processes [1]. Another study on the Yogyakarta Customs Office also shows that the development of ZI must be viewed in terms of its effectiveness in promoting accountability and service quality, not merely in terms of administrative completeness [2]. The development of Integrity Zones has a positive impact on the quality of public services, perceptions of anti-corruption efforts, and organizational performance. These findings underscore the importance of evaluating the development of Integrity Zones not only from the perspective of internal organizational factors but also from the public's perceptions of integrity and the quality of services received [3].

Service users' perceptions are crucial because the public's experiences can reveal aspects of service delivery that are not always apparent from internal evaluations. Research on the ZI at the Palangka Raya City Social Services Agency highlights service quality and bureaucratic responsiveness as key components of ZI implementation discussions [4]. Meanwhile, an evaluation of the ZI at the Malang City Regional Inspectorate showed that commitment to and the conduct of evaluations are linked to a work unit's ability to meet the demands of ZI development [5]. In another study, the implementation of the ZI at the West Surabaya Samsat was also examined in terms of public service, resources, employee commitment, and organizational readiness [6].

In the ZI development survey used in this study, service users' perceptions were measured through two dimensions: the Anti-Corruption Perception Index (IPAK) and the Service Quality Perception Index (IPKP). The IPAK reflects perceptions regarding non-discriminatory service, adherence to procedures, and the absence of demands for bribes, illegal fees, and brokerage. The Service Quality Perception Index (IPKP) reflects users' experiences regarding information, requirements, procedures, processing time, costs, convenience of facilities, response speed, and access to consultation and complaint channels.

The issue is that index values presented in aggregate form may oversimplify variations in respondents' answers. Two respondents may yield similar overall scores but exhibit different response patterns across indicators. Therefore, clustering respondents based on the similarity of their response patterns can provide a more specific and detailed picture. A clustering approach can be used to examine differences in rating patterns at the respondent level. Suprianto applied K-Means and DBSCAN to segment respondents in a survey on perceptions of public service quality. The study showed that clustering respondents can provide a more detailed picture than relying solely on aggregate service scores [7]. K-Means has also been applied to various datasets related to evaluation and service delivery, such as clustering the performance of training institutions [8], segmenting medical records based on service characteristics [9], and clustering medical records based on disease type [10].

K-Means was chosen because it is suitable for forming clusters based on the similarity of characteristics, whereas agglomerative clustering provides a hierarchical perspective through the process of merging clusters. The application of K-Means to service user data and social data has also been conducted in several studies, including on users of KUA services [11], data on individuals facing social welfare issues in North Sumatra [12], and district/city poverty indicators [13]. For the hierarchical approach, Agglomerative Clustering has been used to group provinces based on education indicators [14] and toddler health indicators [15].

Given this context, this study focuses on the following questions: What are the patterns of respondent segmentation based on the 13 IPAK and IPKP indicators, and how do the results

of K-Means compare to those of Ward's Agglomerative Clustering? The research objectives are to generate respondent segmentation, to describe the characteristics of each group, and to assess the level of agreement between the results of the two clustering approaches. The novelty of this study lies in the use of data on public perceptions of ZI development at the respondent level by combining anti-corruption and service quality indicators into a single segmentation process.

Literature Review

2.1 Integrity Zones in Public Service

Integrity Zones relate to improvements in governance and service quality within government work units. The reviewed literature indicates that the development of Integrity Zones does not stop at program establishment but is linked to changes in service processes, oversight, and organizational commitment [1], [2], [4], [5], [6], [16]. From the perspective of service users, perception surveys provide information on how service practices are received by the public. Therefore, survey data can be treated not only as a source of index values but also as data that captures patterns of assessment among respondents.

2.2 Anti-Corruption Perception Index and Service Quality Perception Index

The assessment of Integrity Zone development in government agencies is generally conducted through two main dimensions: the Anti-Corruption Perception Index (IPAK) and the Service Quality Perception Index (IPKP). The Anti-Corruption Perception Index is used to measure public perception of the integrity of service delivery, which includes non-discriminatory service, adherence to procedures, freedom from gratuities, freedom from illegal fees, and the absence of brokerage practices. The presence of these indicators demonstrates that the aspect of integrity is an integral part of the quality of public services [4], [5].

Meanwhile, the Service Quality Perception Index assesses service quality based on eight indicators: availability of service information, appropriateness of requirements, ease of procedures, timeliness of service, appropriateness of costs, comfort of facilities and infrastructure, speed of staff response, and ease of access to consultation and complaint services. The combination of the IPAK and the IPKP provides a more comprehensive picture of public perceptions regarding the implementation of the Integrity Zone, as these two indices complement each other in assessing both integrity and service quality simultaneously [1], [2].

2.3 K-Means Clustering

K-Means is a partitioning clustering method that divides data into a number of groups based on proximity to the centroid. The process begins with determining initial centers, calculating distances, forming groups, and then updating the centroids until convergence is achieved. This method is widely used for segmentation because the procedure is relatively simple and the group results can be summarized using the mean value of each variable [17], [11], [12], [13], [18], [19]. In the context of community-based decision-making, Utomo, Adi, and Nurhayati (2023) combined K-Means with Fuzzy Learning Vector Quantization to cluster the criteria provided by community members. The study demonstrated the application of clustering to community assessment data, although the purpose of the analysis and the combination of algorithms differed from those in this study [20].

In this study, K-Means was used to form three groups of respondents. Centroid initialization was performed using k-means++, and the Euclidean distance was used after all indicators were normalized. This approach ensures that differences in scale do not cause any particular indicator to dominate the distance calculations. Kusumaningrum et al. (2024) combined Sentence-BERT and K-Means to identify and cluster topics in social media posts regarding mangrove ecosystem conservation. That study demonstrated the use of K-Means to identify cluster patterns in unlabeled data, although the data representation and the purpose of the analysis differed from those in this study. Unlike that text-based approach, this study applies K-Means to numerical

survey data to identify patterns in public perceptions regarding the development of the Integrity Zone [21].

2.4 Agglomerative Clustering

Agglomerative clustering is a type of hierarchical clustering. Each observation is initially considered a single cluster; then, the closest clusters are gradually merged until a hierarchical structure is formed. This structure can be visualized through a dendrogram. One of the linkage approaches used in previous studies is Ward's method, which selects the merger that results in the smallest increase in cluster variance [14], [15].

2.5 Clustering in Public Services

The K-Means algorithm has been applied to various types of data related to service delivery and performance evaluation. Iqbal and Budianto used K-Means to cluster training and course institutions based on performance characteristics, such as instructor quality, facilities and infrastructure, management, and graduate outcomes. The clustering results formed groups of institutions with distinct performance characteristics[8]. In the health sector, Padilla et al. used K-Means to segment patient data based on visit times and service characteristics as a basis for developing service strategies [9]. Rahmawati et al. also applied K-Means to cluster the satisfaction levels of BPJS Kesehatan users in Binjai City based on facility characteristics, service personnel, and the users' geographic regions [22].

The K-Means approach was also applied by Aulia et al. to cluster medical record data based on age, blood pressure, and disease diagnosis. This study demonstrated that the clustering process can be used to identify groups with distinct characteristics and subsequently utilized to support healthcare management [21]. In the context of public services, Suprianto employed K-Means and DBSCAN to cluster respondents based on their perceptions of service quality. The study emphasized that segmentation can reveal differences in perception that are not always apparent through aggregate index values [7].

These studies demonstrate that clustering can be applied to healthcare data with diverse variable characteristics. However, most studies still focus on institutional performance, patient characteristics, medical records, or general perceptions of service quality. This study adopts a different approach by combining indicators of anti-corruption perceptions and service quality within the context of Integrity Zone development.

2.6 Previous Research and Research Gaps

Several previous studies have applied clustering methods to various social and public service fields. However, the research subjects, variables used, and analytical approaches applied differ from those in this study. A summary of previous studies is presented in Table 1.

Table 1. Summary of Previous Research

Researcher	Method	Research Object	Key Findings	Research Gaps
Novaldi & Wijayanto (2023)	Agglomerative Hierarchical and K-Means	Quality of Indonesian Youth	Ward's Method produces the best clusters based on internal validation and stability	Did not use data on public perceptions of the Integrity Zone
Widjaja et al. (2023)	K-Means	Marketplace Sentiment in Indonesia	Successfully identified sentiment clusters and popular topics	Uses text data, not public service survey data
Yusuf et al. (2025)	K-Means and Hierarchical Clustering	Regional well-being in West Java	Able to identify disparities in well-being across regions	Does not integrate the IPAK and IPKP indicators
Suprianto (2026)	K-Means and DBSCAN	Perceptions of public service quality	Produces respondent segmentation based on service quality characteristics	Did not include the anti-corruption perception dimension in the analysis

This study	K-Means and Agglomerative Clustering	Public perceptions of the Integrity Zone	Segmentation based on 13 IPAK and IPKP indicators	Addressing the limitations of previous studies

Based on previous studies, the K-Means algorithm has been used in various contexts, ranging from institutional performance evaluation, health services, medical records, to perceptions of public service quality [7], [8], [9], [10], [23]. Suprianto's study is most closely related to this research because both conduct respondent segmentation based on service perception data. However, that study used public service quality indicators and compared K-Means with DBSCAN, whereas this study incorporates both the anti-corruption perception and service quality dimensions simultaneously. Other studies have primarily used institutional characteristic data or medical data, resulting in different objects and variables [8], [9], [10].
Thus, this study aims to fill that gap by segmenting public perceptions of the development of the Integrity Zone using 13 indicators, consisting of five Anti-Corruption Perception Index (IPAK) indicators and eight Service Quality Perception Index (IPKP) indicators. The use of K-Means and Agglomerative Clustering allows cluster patterns to be examined through two distinct clustering approaches, enabling a more detailed analysis of respondents' perceptual characteristics.

Research Methodology

3.1 Research Design

This study employs a quantitative approach using data mining methods to segment public perceptions regarding the development of the Integrity Zone at the Medan Health Quarantine Center. The clustering method was chosen because it can group respondents based on the degree of similarity in their perceptions without requiring predefined class labels. This study applied the K-Means and Agglomerative Clustering algorithms to compare the resulting clustering patterns and identify the characteristics of each respondent segment [1], [6], [24].

3.2 Research Location and Data Sources

The study was conducted at the Medan Health Quarantine Center using data from the 2025 External Survey on the Assessment of Integrity Zone Development toward a Corruption-Free Zone (WBK) and a Clean and Service-Oriented Bureaucracy Zone (WBBM).
The research data consisted of 1,046 respondents who had used the services at that work unit. The survey instrument used a six-point Likert scale, namely:

- Strongly Disagree
- Disagree
- Somewhat Unsatisfactory
- Somewhat Appropriate
- Agree
- Very Appropriate

The use of respondent data directly as the unit of analysis was chosen so that the resulting groupings would reflect variations in perception among service users, rather than just aggregate average values. This type of segmentation approach is also used in research on perceptions of public service quality, where the overall index value does not necessarily reveal differences in assessment patterns among respondents [11].

3.3 Research Variables

The research variables consist of two main dimensions, namely the Anti-Corruption Perception Index (IPAK) and the Service Quality Perception Index (IPKP). In total, there are 13 indicators used as attributes in the clustering process, comprising five IPAK indicators and eight IPKP indicators [1], [6].

Table 2. Research Variables

Dimensions	Code	Indicator
IPAK	IPAK1	Services are provided without discrimination of any kind
IPAK	IPAK2	Services are provided in accordance with procedures and without fraud
IPAK	IPAK3	Officials do not request compensation in the form of money, goods, or benefits
IPAK	IPAK4	Officials do not engage in illegal extortion
IPAK	IPAK5	There is no brokerage in service delivery
IPKP	IPKP1	Service information is available through both electronic and non-electronic media
IPKP	IPKP2	Service requirements comply with applicable regulations
IPKP	IPKP3	Service procedures are easy to understand and follow
IPKP	IPKP4	Service turnaround times meet established standards
IPKP	IPKP5	Service rates or fees in accordance with regulations
IPKP	IPKP6	Infrastructure and online service systems provide convenience
IPKP	IPKP7	Service staff or systems provide a quick response
IPKP	IPKP8	Consultation and complaint services are easily accessible

3.4 Research Stages

The research was conducted in several stages, including data collection, data cleaning, variable selection, data normalization, determination of the optimal number of clusters, implementation of the K-Means and Agglomerative Clustering algorithms, evaluation of cluster quality, and interpretation of segmentation results [4], [6], [14].

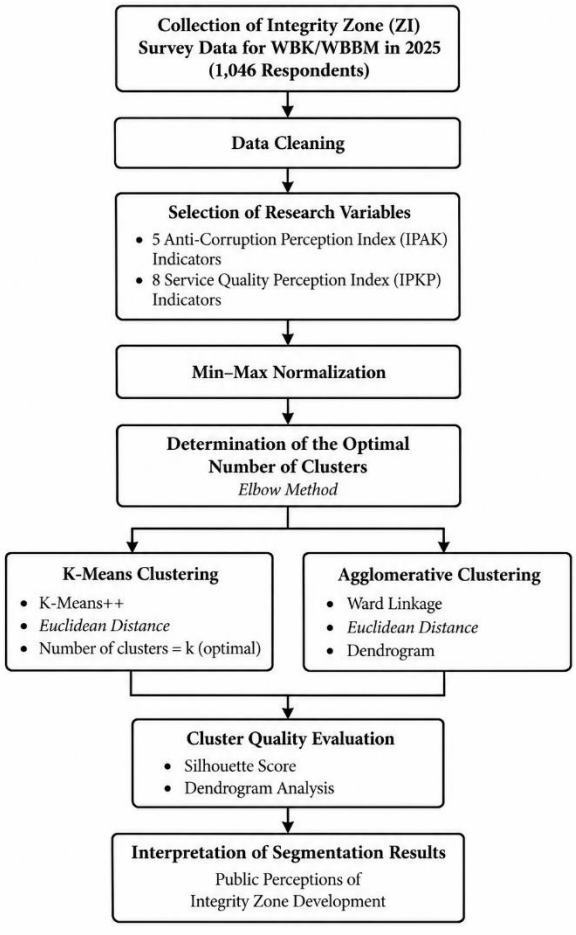


Figure 1. Research Flowchart

3.5 Data Cleaning

The data cleaning stage was conducted to ensure data quality before the analysis process began. Activities included checking for duplicate data, identifying missing values, and verifying the consistency of respondents' answers across all IPAK and IPKP indicators. Data that did not meet completeness criteria or fell outside the 1–6 Likert scale range were excluded from the analysis [6], [17].

Additionally, this study uses only 13 perception indicators as cluster-forming attributes. Demographic variables are not used in the clustering process but can be utilized during the result interpretation stage to explain the characteristics of each respondent segment [1], [6].

3.6 Data Normalization

All indicators were normalized using Min-Max Normalization so that their values fell within the range of 0 to 1. This step was taken because both algorithms used rely on distance calculations. Differences in the ranges between indicators could cause certain variables to have a greater influence on the clustering results. The use of Min-Max on service survey data has also been observed in studies on public service clustering [17].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

In the equation above, x' is the normalized value, x is the original value of a variable, x_{min} represents the minimum value, and x_{max} represents the maximum value. This process aims to ensure that all indicators contribute equally to cluster formation [17], [18].

Normalization is necessary to ensure that differences in the ranges between attributes do not cause certain attributes to be more dominant in distance calculations. Asyifa and Novelan used Min-Max Normalization to map attributes to the range of 0 to 1 prior to the K-Means process so that each attribute has a more uniform scale [23]. In this study, the same approach was used because all IPAK and IPKP indicators were used simultaneously in the clustering process.

3.7 Determining the Optimal Number of Clusters

The number of clusters was determined using the Elbow Method by analyzing changes in the Within-Cluster Sum of Squares (WCSS) for several alternative cluster counts. The resulting elbow point was used as a reference for determining the most optimal number of clusters [4], [12].

$$WCSS = \sum_{k=1}^{k} \sum_{i \in C_k} \|x_j - \mu_k\|^2$$

The initial number of clusters was examined from k=2 to k=10 using WCSS. The greatest decrease in WCSS occurred from k=2 to k=3; thereafter, the curve became flatter. This pattern served as the basis for selecting three clusters for the main analysis. The Silhouette coefficient was also calculated for each value of k to provide additional information. In this dataset, the highest Silhouette value occurred at k=7, namely 0.6005. However, since the research objective was not only to find the highest Silhouette value but also to obtain a concise segmentation that is easily comparable across algorithms, k=3 was retained based on the Elbow curve pattern.

Determining the number of clusters is a crucial step because the number of groups will influence the resulting segmentation pattern. The study by Asyifa and Novelan tested several values of k and evaluated the clustering results using the Silhouette Coefficient to assess the quality of group separation [23]. This study used the Elbow method to identify candidate numbers of clusters, then evaluated the clustering results using the Silhouette Score.

3.8 K-Means Clustering

K-Means is a partition-based clustering algorithm that groups data based on their proximity to the cluster center (centroid). The clustering process is performed iteratively by determining initial centroids, calculating distances between objects, and updating the centroids until convergence is achieved [2], [12], [13].

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2$$

This equation shows that the K-Means algorithm seeks to minimize the total squared distance between each data point and its cluster centroid. The smaller the value of this objective function, the higher the level of homogeneity among members within a cluster [12], [18].

In this study, the K-Means algorithm was implemented using the k-means++ initialization method to improve the stability of the clustering results and reduce the likelihood of getting stuck in local optima. The number of clusters was determined using the Elbow Method so that the resulting segmentation would be more representative of the characteristics of public perception regarding the development of the Integrity Zone [4], [18].

3.9 Agglomerative Clustering

Agglomerative clustering is a hierarchical clustering method that forms data groups through a process of gradually merging individual objects into larger clusters based on their similarity [19], [24].

This study uses Ward's Method. Ward's criterion selects the merger that results in the smallest increase in cluster variance. This approach is used to ensure that members within a cluster remain relatively homogeneous. In general, Ward's criterion relates to the change in the Sum of Squared Error (SSE) resulting from the merger of two groups [15]..

$$\Delta SSE = \frac{n_A n_B}{n_A + n_B} \|\mu_A - \mu_B\|^2$$

In this equation, ΔSSE represents the change in the Sum of Squared Error resulting from the merging of two clusters. The variables n_A and n_B denote the number of members in each cluster, while μ_A and μ_B represent the centroids of the two clusters [14], [18].

The clustering results are visualized using a dendrogram to show the hierarchical relationships among objects and to help determine the most representative number of clusters [19], [25].

3.10 Cluster Quality Evaluation

The quality of the clustering results is evaluated using the Silhouette Score. This metric examines the relationship between the compactness of a data point within its own cluster and its distance from other clusters. Its value ranges from −1 to 1; a higher value indicates that objects tend to be closer to their own cluster than to other clusters [17], [24].

$$S(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))}$$

In this equation, $a(i)$ represents the average distance of a data point from other members in the same cluster, while $b(i)$ is the average minimum distance to other clusters. The Silhouette Score ranges from −1 to 1, where values closer to 1 indicate better clustering quality [15], [24].

These evaluation metrics were used to compare the performance of the K-Means and Agglomerative Clustering algorithms in segmenting public perceptions regarding the development of the Integrity Zone. The Silhouette Score was used to examine the relationship between the cohesion of data within a cluster and its separation from other clusters. A value closer to 1 indicates that the data is closer to its own cluster than to other clusters. The use of the Silhouette Score as a clustering evaluation metric was also applied by Asyifa and Novelan in evaluating K-Means results [23].

3.11 Research Software

The entire process—including data processing, implementation of the clustering algorithm, evaluation of the clustering results, and visualization—was carried out using the Python programming language via the Google Colaboratory (Google Colab) cloud-based computing environment. Data management and manipulation were performed using the pandas library; numerical computations were performed using NumPy; the K-Means algorithm was implemented and clustering results were evaluated using scikit-learn; dendrograms were generated for the Agglomerative Clustering algorithm using SciPy; and analysis results were visualized using Matplotlib [6], [14], [18].

Google Colab was chosen because it provides a Python programming environment that is accessible via a web browser without requiring the installation of a local computing environment. Additionally, support for various machine learning and data mining libraries facilitates the structured implementation of both clustering algorithms, the evaluation of clustering results, and the presentation of visualizations to support the interpretation of research findings.

Result and Discussion

4.1 Data Check Results

The results of the data check showed that all 1,046 respondents were usable. No missing values were found in the 13 indicators, and no rows were found to be completely identical. Response values ranged from 1 to 6. These conditions allowed the analysis to be conducted without imputation and without reducing the number of respondents due to incomplete data.

4.2 Determination of the Number of Clusters

Table 3. Determination of the Number of Clusters

k	WCSS	Silhouette
2	238.555	0.5255
3	150.260	0.5515
4	132.140	0.5611
5	114.726	0.5698
6	102.378	0.5913
7	93.524	0.6005
8	85.590	0.5962
9	82.714	0.5660
10	76.146	0.5971

The table shows that the WCSS decreased from 238.555 at k=2 to 150.260 at k=3. After k=3, the WCSS continued to decrease but at a slower rate. Since the study required a concise and consistent number of clusters for both algorithms, three clusters were used in the next stage. The silhouette at k=3, which is 0.5515, serves as the evaluation metric for the main K-Means model.

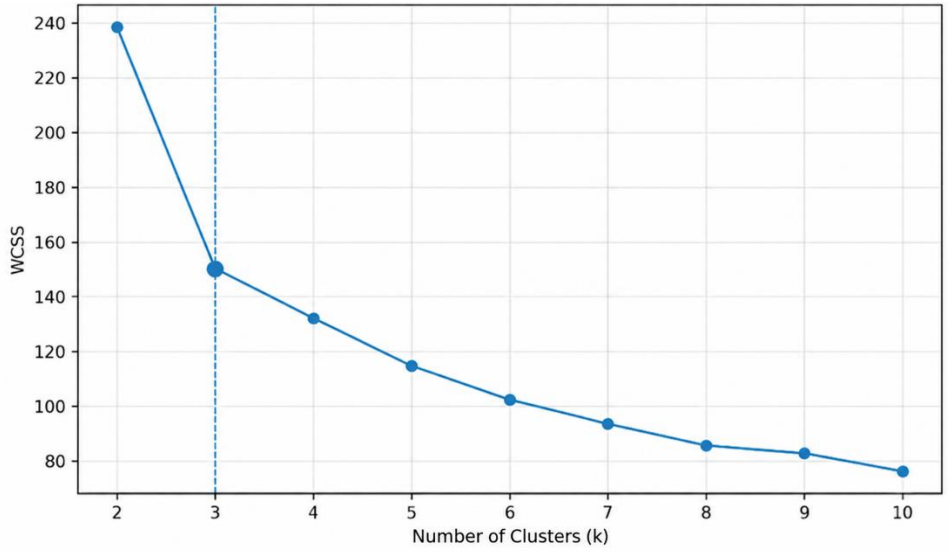


Figure 2. The Elbow Method for determining the number of clusters

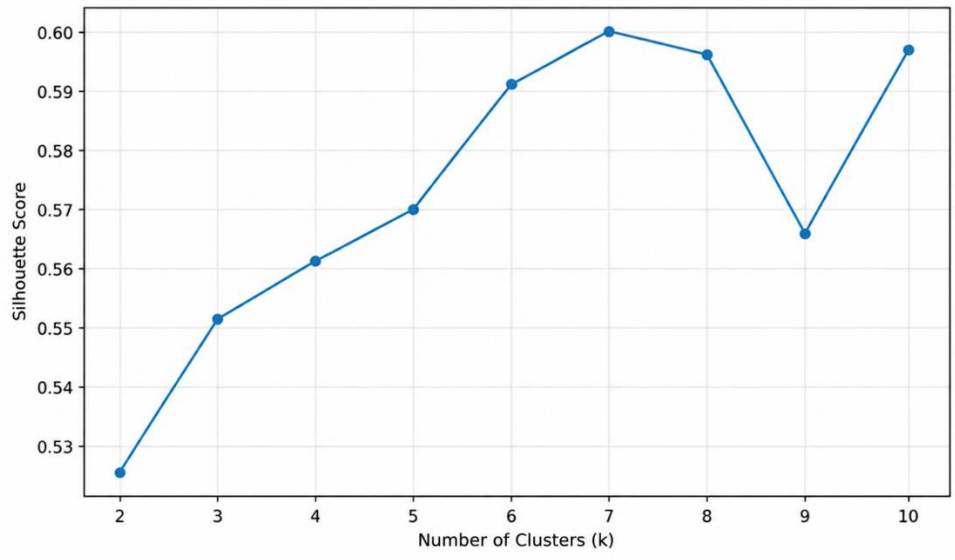


Figure 3. Silhouette score for various numbers of clusters

4.3 Hasil K-Means

Table 4. K-Means Results

Cluster	Respondents	Percentage (%)	Average IPKP	Average IPAK	Average of 13 indicators
1	338	32.31	5,121	5,197	5,150
2	558	53.35	5,909	5,962	5,929
3	150	14.34	3,833	5,308	4,400

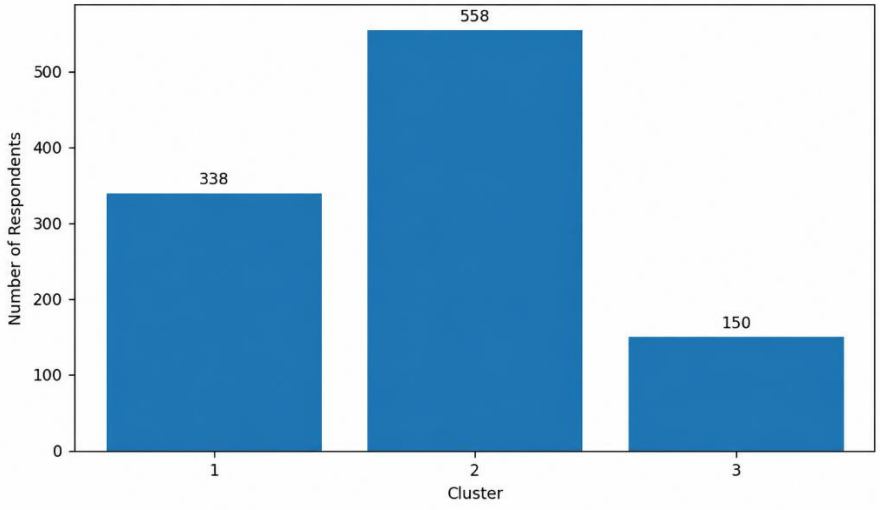


Figure 4. Distribution of respondents based on K-Means (k=3)

Based on the indicator profiles, Cluster 2 shows high ratings on both dimensions. Cluster 1 scores lower than Cluster 2, but both dimensions still remain above the midpoint of the scale. A different pattern emerges in Cluster 3. The IPKP score drops quite significantly, while the IPAK score remains relatively high. This means that this group does not simply give low ratings across all aspects but exhibits a gap between their perceptions of service quality and their perceptions of anti-corruption efforts. This pattern is one of the insights that is difficult to discern if the data is merely summarized into a single index value.

Table 5. Profile of indicators representing the information aspect

Cluster	IPKP1	IPKP4	IPKP6	IPKP7	IPAK1	IPAK3	IPAK5
1	5.04	5.03	4.86	5.07	5.15	5.25	5.20
2	5.84	5.92	5.85	5.94	5.95	5.97	5.97
3	3.76	3.90	3.81	3.89	5.25	5.31	5.37

The profile table was selected to show indicators representing the aspects of information, service time, convenience, staff responsiveness, and several integrity indicators. In Cluster 3, for example, IPKP4 and IPKP6 stood at 3.90 and 3.81, respectively, while IPAK3 and IPAK5 reached 5.31 and 5.37, respectively. These differences reinforce the finding that service quality and perceptions of anti-corruption do not always follow the same pattern.

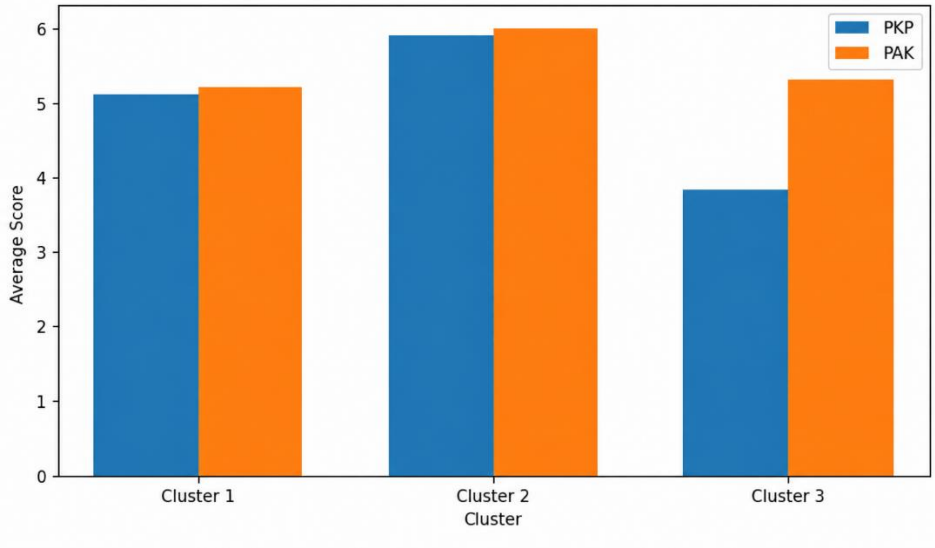


Figure 5. Average IPKP and IPAK profiles by cluster.



Figure 6. Indicator profiles for each cluster.

4.4 Results of Agglomerative Clustering

Table 6. Results of Agglomerative Clustering

Cluster	Respondents	Percentage (%)	Average IPKP	Average IPAK	Average of 13 indicators
1	455	43.50	5,232	5,354	5,279
2	145	13.86	3,816	5,334	4,400
3	446	42.64	5,984	5,987	5,985

Agglomerative Ward analysis also yielded three main patterns. Cluster 3 had an average IPKP of 5.984 and an IPAK of 5.987, with 446 respondents. Cluster 1 consisted of 455 respondents with an average IPKP of 5.232 and an IPAK of 5.354. Meanwhile, Cluster 2 consists of 145 respondents with an average IPKP of 3.816 and an IPAK of 5.334. Thus, the structure of the Ward results shows a pattern consistent with K-Means: there are groups with high scores on both dimensions, groups with moderate scores, and groups that differ primarily in terms of service quality.

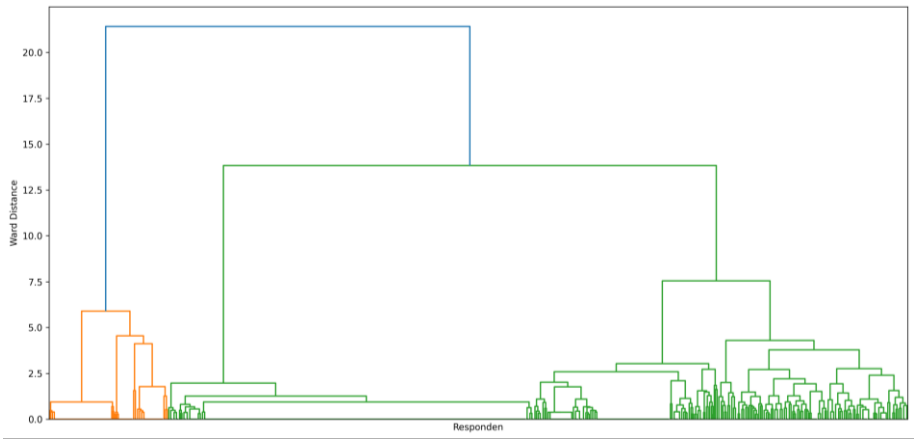


Figure 7. Agglomerative Clustering Dendrogram Using Ward's Method.

4.5 Comparison of K-Means and Agglomerative Ward

Table 7. Comparison of K-Means and Agglomerative Ward

Method	Number of Clusters	Silhouette	ARI	NMI
K-Means	3	0.5515	0.6539	0.7189
Agglomerative Ward	3	0.5093	0.6539	0.7189

K-Means produced a Silhouette value of 0.5515, while Agglomerative Ward produced 0.5093. Both values indicate that the resulting cluster structure can be distinguished to a certain extent based on the Silhouette measure. The difference in results is evident not only in the scores but also in the distribution of respondents. K-Means produced the largest cluster with 558 respondents, while Ward's algorithm produced two large clusters with 455 and 446 respondents, respectively.

An ARI value of 0.6539 and an NMI value of 0.7189 indicate a degree of agreement between the results of the two algorithms, but the respondents' labels are not entirely the same. The most easily observable similarity lies in the profile pattern: both methods identified a group with a low IPKP but a consistently high IPAK. This suggests that the pattern is not solely the result of a single algorithm

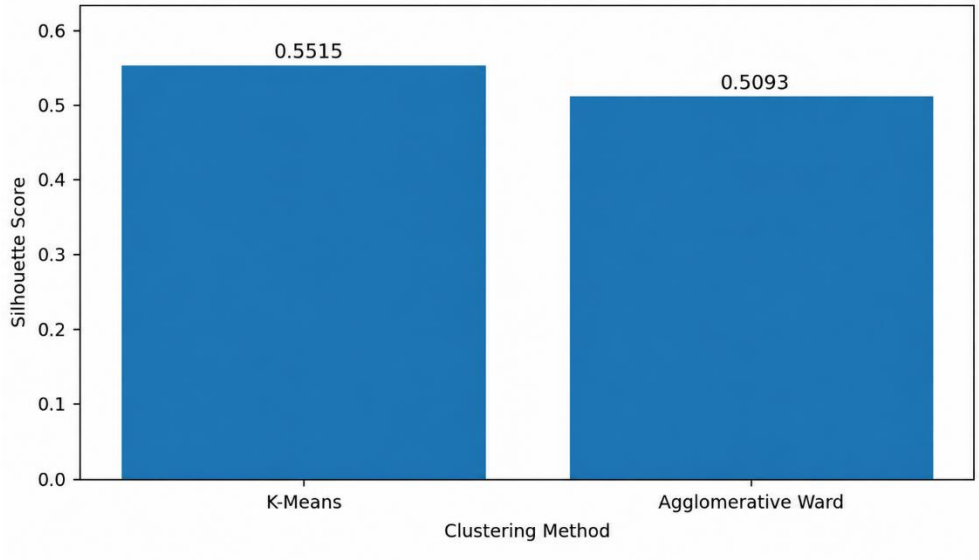


Figure 8. Comparison of Silhouette Scores.

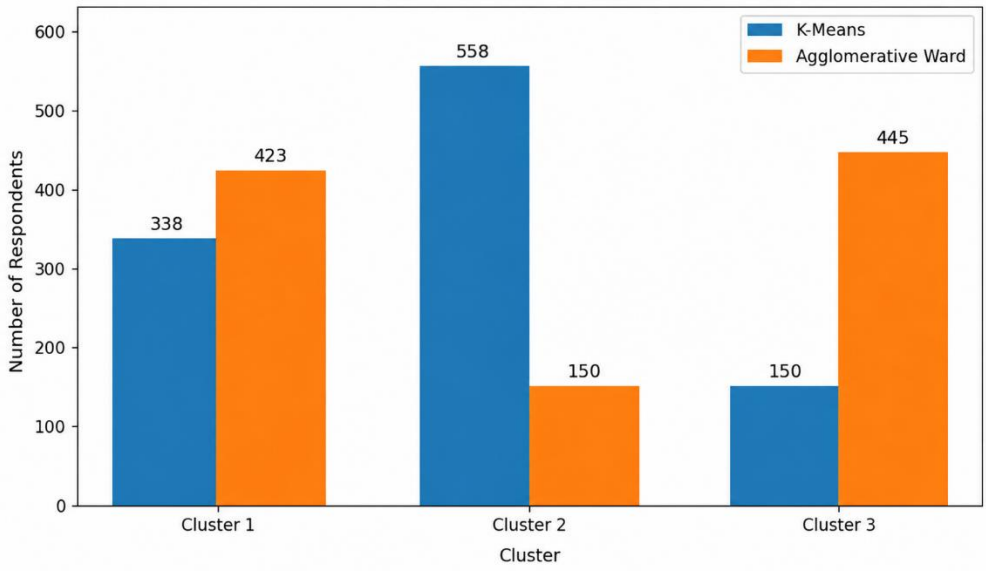


Figure 9. Comparison of K-Means and Agglomerative Ward Respondent Distributions.

4.6 Discussion

The research results show that respondents do not form a single homogeneous perception group. Most respondents fall into a group with high ratings for both service quality and anti-corruption, but there are other groups with more specific patterns. Findings in K-Means Cluster 3, for example, show that perceptions of service quality are far below perceptions of anti-corruption. The same pattern emerges in the Ward method, although the number of members differs.

From an evaluation perspective, these results support the use of clustering as a complement to index analysis. The study by Hariyanto et al. used K-Means to identify patterns of public satisfaction based on service indicators [17], while Suprianto demonstrated that respondent segmentation can provide insights not visible in aggregate indices [7]. This study expands on that approach by incorporating anti-corruption indicators alongside service quality indicators. Thus, segmentation not only answers the “ ” of who gives high or low ratings but also reveals the combination of rating patterns across dimensions.

There is one important note regarding the selection of the number of clusters. If only the Silhouette coefficient is used, k=7 yields the highest value, namely 0.6005. However, the k=7 structure produces a segmentation that is more detailed than what is required for the main analysis of this study. The Elbow curve shows the most significant change at k=3; therefore, three clusters are retained to make the results easier to interpret and compare with the Agglomerative Ward method. This decision should be interpreted as an analytical choice based on a combination of considerations, not as a claim that k=3 is the only possible solution.

For the ZI evaluation, the segmentation results can help guide the interpretation of data across respondent groups. Groups with relatively low IPKP and relatively high IPAK indicate that the aspect of integrity is perceived differently from the experience of service quality. Therefore, follow-up evaluations should not treat all respondents as a single group with identical needs. The clustering results can serve as a starting point for identifying the service indicators that form these patterns through further analysis.

Conclusion

This study successfully segmented public perceptions of the Integrity Zone development at the Medan Health Quarantine Center using 1,046 respondents and 13 IPAK and IPKP indicators. Based on the Elbow rule, three clusters were used for the main analysis. K-Means yielded a Silhouette Score of 0.5515, while Agglomerative Ward yielded 0.5093.

K-Means formed three groups with fairly distinct characteristics: Cluster 2 is the largest group with high ratings for service quality and anti-corruption; Cluster 1 has moderate ratings on both dimensions; and Cluster 3 has a lower IPKP but a relatively high IPAK. Agglomerative Ward produced a similar pattern, although the number of members in each cluster differed. ARI values of 0.6539 and NMI values of 0.7189 indicate structural consistency between the two approaches, but the distribution of respondents is not identical.

The results show that analyzing perceptions at the respondent level can provide additional information compared to aggregate index values. Further research could link the formed clusters to characteristics such as service type, work area, age group, or other demographic variables during the interpretation stage, as well as test the stability of the clusters using different survey periods.

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