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CLUSTERING OF CONSUMER PERCEPTIONS TOWARD PROCESSED CHICKEN MEAT PRODUCTS TO SUPPORT REGIONAL FOOD SECURITY

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ABSTRACT: *This study aims to classify micro, small, and medium enterprises (MSMEs) in the agroindustry sector based on their performance and sustainability characteristics using the K-Means clustering method. The analysis was conducted to identify homogeneous groups of MSMEs that share similar attributes in innovation, efficiency, value addition, and sustainable practices. The optimal number of clusters was determined using the Dunn Index, which evaluates the compactness and separation of clusters. The results indicate that the highest Dunn Index value was obtained for three clusters (0.24), compared to two clusters (0.23), four clusters (0.22), and five clusters (0.17). This finding suggests that a three-cluster model provides the most optimal structure, balancing within-cluster cohesion and between-cluster separation. The visualization of the clustering results further demonstrates distinct groupings among MSMEs, corresponding to high-performing, moderate, and developing enterprises. These results provide valuable insights for policymakers and stakeholders in designing targeted strategies to enhance competitiveness and sustainability in the agroindustry sector.*

Keywords: *Agroindustry, Cluster Validation. Competitiveness, Dunn Index,*
K-Means Clustering

1. INTRODUCTION

Food security has become an increasingly critical issue across regions, particularly in Banten Province, which relies heavily on the agricultural sector to sustain community livelihoods and economic stability. The province exhibits diverse patterns of consumption and processing of chicken-based food products (Banten Province, 2020; Ministry of Industry, 2015). Processed chicken meat is among the most preferred food commodities and serves as a major source of animal protein that supports overall nutritional security (Bristow & Sebastian, 2001). In this context, understanding consumer behavior and preferences in purchasing and consuming processed chicken products is vital for developing effective strategies to enhance regional food security.

Regional food security is strongly influenced by consumer preferences and perceptions of processed chicken meat products. These preferences guide policymakers and business actors in ensuring a stable, high-quality, and affordable food supply. Consumer perceptions of product safety also play a pivotal role in sustaining and expanding the processed chicken meat industry along the supply chain (Grunert, 2005). Factors such as quality, price, poultry health, and brand reputation shape consumer purchasing behavior. Identifying consumer groups through segmentation enables more effective targeting of products and marketing strategies based on specific consumer needs. Studies on food safety and consumer behavior highlight the importance of understanding consumer perceptions when formulating policies that contribute to a sustainable food system (de Jonge et al., 2004).

While national food trends provide a broad overview, regional variations—such as differences in economic conditions, cultural preferences, and access to food resources-significantly influence consumer behavior toward processed chicken consumption (Martins & Pato, 2019). Without region-specific data on processed food products, policymakers may face difficulties in designing effective interventions to ensure both food safety and security. Chicken meat remains a key source of animal protein and is often chosen due to its affordability, accessibility, and ease of preparation (Shan et al., 2017). Food security encompasses the dimensions of availability, access, utilization, and stability of sufficient, safe, and nutritious food for all people. In this regard, processed chicken meat products play an important role due to their high nutritional value, versatility in processing, and increasing consumer demand (Kovacheva et al., 2024).

Previous research has predominantly emphasized economic factors—such as income, capital, and price—as key determinants of consumer purchasing behavior, while non-economic factors like health awareness and product certification have received less attention (Sabaté & Soret, 2014). Nevertheless, consumer confidence in the safety and quality of processed products is closely related to perceptions of content and composition, which in turn affect purchasing decisions (Sedera et al., 2023). Prior studies have shown that consumer segmentation varies by price sensitivity, brand attachment, and ethical concerns, including humane production systems (Roascio-Albistur et al., 2019; Boito et al., 2021). Other studies emphasize the importance of service quality, freshness, presentation, and product variety in influencing satisfaction and loyalty (Naini et al., 2022; Rochmatulaili, n.d.). To capture these diverse consumer perceptions, cluster analysis has become a valuable statistical method for grouping objects based on shared characteristics. It has been widely applied in various domains, such as evaluating health services (Suhaeni et al., 2018) and allocating aid funds to small and medium-sized enterprises (Ekawati & Yulis, 2013). Among existing clustering algorithms, the K-Means method is one of the most widely used due to its simplicity and fast convergence (Trenggonowati et al., 2019).

Therefore, this study employs the K-Means clustering technique to analyze consumer perceptions of processed chicken meat products, identify key determinants of purchasing behavior, and determine the optimal number of consumer clusters through hierarchical validation.

2. MATERIALS AND METHODS

This study, as illustrated in Figure 1 (Research Framework), adopts a mixed-methods approach that integrates both qualitative and quantitative research methods. The qualitative component was used to identify variables relevant to consumer perceptions of processed chicken meat quality through questionnaires and field observations. These qualitative insights helped define the main indicators for clustering consumer preferences and behaviors. The quantitative component was then employed to process the collected data statistically using the *R-software*, enabling the identification of optimal cluster groupings and interpretation of consumer segmentation results. The outcomes of this analysis provide strategic insights for designing targeted marketing approaches in the processed chicken meat industry.

The research was conducted in Cilegon City, Banten Province, Indonesia, where the processed chicken meat industry operates as part of small-scale enterprises supported by the Cilegon City Government. These industries produce a variety of products such as meatballs, nuggets, and sausages. The study was carried out over a period of six months, from April to August 2024, with data collection conducted periodically each week to ensure data consistency and reliability.

Two types of data were used in this study: primary data and secondary data.

a. Primary data were obtained through direct observation and structured interviews with business owners and production managers of processed chicken meat industries in Cilegon City. These observations provided insight into product quality, production processes, and consumer feedback.
b. Secondary data were collected from consumer questionnaires that captured respondents' perceptions, preferences, and purchasing decisions regarding processed chicken meat products. The questionnaire was distributed to consumers who had purchased or consumed chicken-based processed products such as nuggets, sausages, and meatballs. The variables measured included product quality, price, brand trust, safety perception, and purchasing frequency.

Data analysis was conducted using the K-Means clustering method within the R statistical software environment. The clustering process involved several stages:

a. Data Preprocessing: Questionnaire responses were first coded numerically and standardized to ensure uniform data scales. Missing or inconsistent data were cleaned prior to analysis.
b. Variable Selection: Variables related to consumer perceptions—such as product quality, price sensitivity, brand trust, and safety assurance—were selected as input features for clustering.
c. Cluster Formation (K-Means): The K-Means algorithm was applied to group consumers into clusters based on similarities in their purchasing behavior and product perceptions. The number of clusters (K) was determined through iterative testing and validation.
d. Cluster Validation: The Dunn Index was used to evaluate the optimal number of clusters by measuring the ratio of minimum inter-cluster distance to maximum intra-cluster distance. The highest Dunn Index value indicates the most distinct and well-separated clusters.
e. Interpretation and Segmentation: Each resulting cluster was analyzed descriptively to identify its unique characteristics—such as demographic tendencies, preference intensity, and perception toward processed chicken meat quality. The results were then used to propose targeted marketing segmentation strategies for the industry.

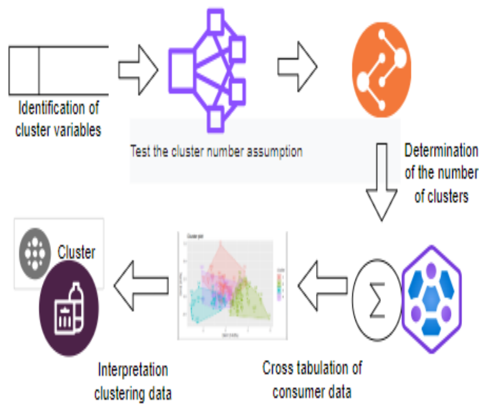


Figure 1. Research Framework

3. RESULTS AND DISCUSSION

This study employed a survey method with a total of 155 respondents drawn from various student populations in Cilegon City and surrounding areas. Data were collected through a structured questionnaire consisting of both closed and open-ended questions designed to capture consumer perceptions and purchasing behaviors toward processed chicken meat products. The collected data were analyzed using descriptive statistical techniques and cluster analysis to identify consumer segmentation patterns.

The clustering analysis in this study was conducted using the K-Means algorithm to segment consumers based on similarities in their perceptions of processed chicken meat products. This method is widely applied in agroindustrial research due to its computational efficiency and its suitability for identifying natural groupings within multidimensional datasets (Nusti et.al, 2021). Prior to cluster formation, the dataset was standardized to ensure that variables measured on different scales contributed equally to the distance calculations. Standardization is particularly important in studies involving consumer perception, where variables such as taste preferences, brand trust, product safety, and packaging aesthetics may possess heterogeneous value ranges (Sari & Wibowo, 2021).

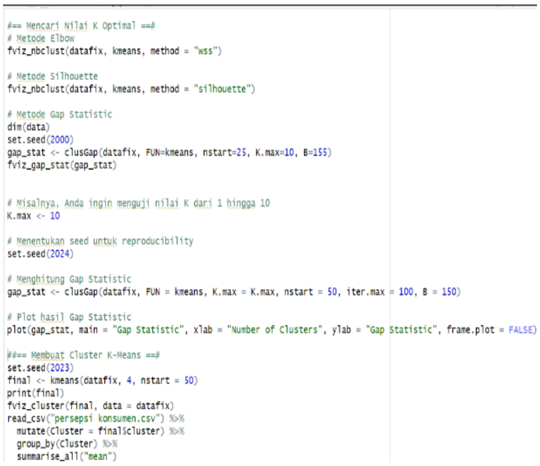
The clustering process was conducted using the R programming environment with the assistance of the *cluster* and *factoextra* libraries. The installation and configuration of these libraries represent the preliminary steps necessary to perform K-Means clustering analysis. These libraries provide essential functions for computing and visualizing cluster structures, making them suitable for exploring consumer perception data.

```r
install.packages("readxl")
install.packages("tidyverse")
install.packages("cluster")
install.packages("ggplot2")
install.packages("factoextra")
install.packages("dplyr")
install.packages("fdm2id")
install.packages("RColorBrewer")
install.packages("NbClust")
install.packages("dplyr_col_modify")

library(readxl)
library(tidyverse)
library(cluster)
library(ggplot2)
library(factoextra)
library(dplyr)
library(fdm2id)
library(RColorBrewer)
library(NbClust)
library(psych)
library(dplyr_col_modify)

#== Mengimport Data ==#
data <- read_csv("persepsi konsumen.csv")
View(data)      # Melihat data
str(data)       # Melihat struktur data
head(data)      # Melihat 5 data teratas
summary(data)   # Deskriptif data

#== Standarisasi Data ==#
str(data)
datafix <- scale (data, center = TRUE, scale = TRUE) # Standarisasi atau scalling data
datafix
```

Figure 2. Library installation process

Figure 2 represents a data preprocessing workflow, which ensures that the input dataset is clean, structured, and standardized before applying clustering techniques. Proper preprocessing enhances the accuracy, validity, and interpretability of clustering results, forming the foundation for meaningful consumer perception analysis.

To determine the optimal number of clusters (K), several statistical validation methods were employed. Gap Statistic method, which compares the logarithm of within-cluster dispersion (WCD) of the observed data against that of reference (random) data. The optimal K-value is indicated by the point where the gap statistic is maximized, suggesting the number of clusters that best represent the data structure.



```r
#== Mencari Nilai K Optimal ==#
# Metode Elbow
fviz_nbclust(datafix, kmeans, method = "wss")

# Metode Silhouette
fviz_nbclust(datafix, kmeans, method = "silhouette")

# Metode Gap Statistic
dim(data)
set.seed(2000)
gap_stat <- clusGap(datafix, FUN=kmeans, nstart=25, K.max=10, B=155)
fviz_gap_stat(gap_stat)


# Misalnya, Anda ingin menguji nilai K dari 1 hingga 10
K.max <- 10

# Menentukan seed untuk reproducibility
set.seed(2024)

# Menghitung Gap Statistic
gap_stat <- clusGap(datafix, FUN = kmeans, K.max = K.max, nstart = 50, iter.max = 100, B = 150)

# Plot hasil Gap Statistic
plot(gap_stat, main = "Gap Statistic", xlab = "Number of Clusters", ylab = "Gap Statistic", frame.plot = FALSE)

##== Membuat Cluster K-Means ==#
set.seed(2023)
final <- kmeans(datafix, 4, nstart = 50)
print(final)
fviz_cluster(final, data = datafix)
read_csv("persepsi konsumen.csv") %>%
  mutate(Cluster = final$cluster) %>%
  group_by(Cluster) %>%
  summarise_all("mean")
```

Figure 3. R code step

The figure 3. shows a series of R code steps used to determine the optimal number of clusters (k) and to perform clustering using the K-Means method. In the first part, the code applies three different approaches to find the best k value, namely the Elbow method (which measures the total within-cluster sum of squares), the Silhouette method (which evaluates the quality of separation between clusters), and the Gap Statistic method (which compares the distribution of the actual data to randomly generated data). After defining the range of k values to be tested and setting set.seed() to ensure reproducibility, the code calculates and displays the Gap Statistic plot as a basis for selecting the optimal number of clusters. Next, the selected k value (for example, k =

4) is used in the kmeans (4) function to form clusters within the dataset. The clustering results are then merged back into the original dataset, and the final step summarizes the mean values of each variable within each cluster to identify the characteristics of the groups formed. Thus, the code provides a complete procedure starting from determining the best number of clusters to analyzing the clustering results.

The K-Means clustering process, visualized in Figure 4, includes several key stages: package installation, data preparation, cluster formation, evaluation, and visualization. This structured approach ensures that the resulting clusters are both statistically valid and interpretable. Data standardization (as shown in Figure 6) was also performed prior to clustering to minimize the influence of differing scales or measurement units among variables, ensuring equal weighting in the distance calculations.

```r
#== Menampilkan Tabel Klasterisasi ==#
dfklaster <- data.frame(data[,1], final$cluster)
row.names(dfklaster) <- c(1:155)
dfklaster
write.csv(dfklaster, file = "hasil cluster persepsi.csv")

#== Membuat Cluster K-Means (3 dimensi) ==#
data_reduced <- read_csv("hasil cluster persepsi.csv")
set.seed(2024)
final_3d <- kmeans(data_reduced, 3)
print(final_3d)

#== Visualisasi Klaster (3 dimensi) dengan Plotly ==#
cluster_data <- data.frame(Cluster = final_3d$cluster, data_reduced)
fig <- plot_ly(cluster_data, x = ~PC1, y = ~PC2, z = ~PC3, color = ~as.factor(Cluster),
               type = "scatter3d", mode = "markers",
               marker = list(size = 5, opacity = 0.8))

fig
```

Figure 4 Steps for creating a cluster

Figure 4. shows a sequence of R code used to display the clustering results and visualize the clusters in a three-dimensional plot. In the first part, the code combines the original dataset with the clustering results (final$cluster) into a new data frame called dfklaster, and then saves it as a CSV file named *"hasil cluster persepsi.csv"* so that it can be analyzed or reused later. Next, the data is reduced to three dimensions (for example, using PCA or selected variables), and the K-Means process is performed again on these three dimensions to produce 3D cluster results (final_3d). Finally, the code visualizes the clusters using Plotly, where each data point is plotted based on three coordinates (PC1, PC2, PC3), and the cluster groups are differentiated by color. This 3D visualization helps the researcher to clearly observe the separation patterns between clusters in an interactive three-dimensional space.

Figure 5 above Cluster with n=2 separates the data into Simplification to help understand the underlying structure of the data, and Over-simplification some important information is lost because only two clusters are used to represent all the variation in the data. Cluster with n=3, identifies sub-groups in the data, in different iris datasets. Three provides a balance between too few and too many clusters, especially if the data has three natural groups. Formation of 4 clusters details the data to help identify sub-groups or more subtle variations in the data and the model overfits the data, capturing noise rather than the patterns that are truly present. Data standardization in figure 6 is essential to standardize data in order to minimize the effects of different scales or units. To understand the quality and performance of the clustering method used, such as k-means, we can use several evaluation metrics and data standardization techniques. Some commonly used metrics include the Elbow method, Silhouette Score, and Dunn Index. The interpretation of the results of the three methods is as follows; The Elbow Method looks for a bend point on the WSS graph, which indicates the optimal number of clusters. Silhouette Score selects the cluster with the highest average Silhouette Score value. Dunn Index selects the cluster with the highest Dunn Index value.

To determine the optimal number of clusters, several internal validation techniques were employed, including the Elbow Method, Silhouette Score, and the Dunn Index. The Dunn Index was given particular emphasis, as it evaluates the ratio between inter-cluster separation and intra-cluster compactness; higher values indicate a more distinct and well-structured clustering result (Andalib, et.al, 2023). This result confirms that a three-cluster configuration provides the most coherent segmentation structure, offering an optimal balance between internal homogeneity and external differentiation.

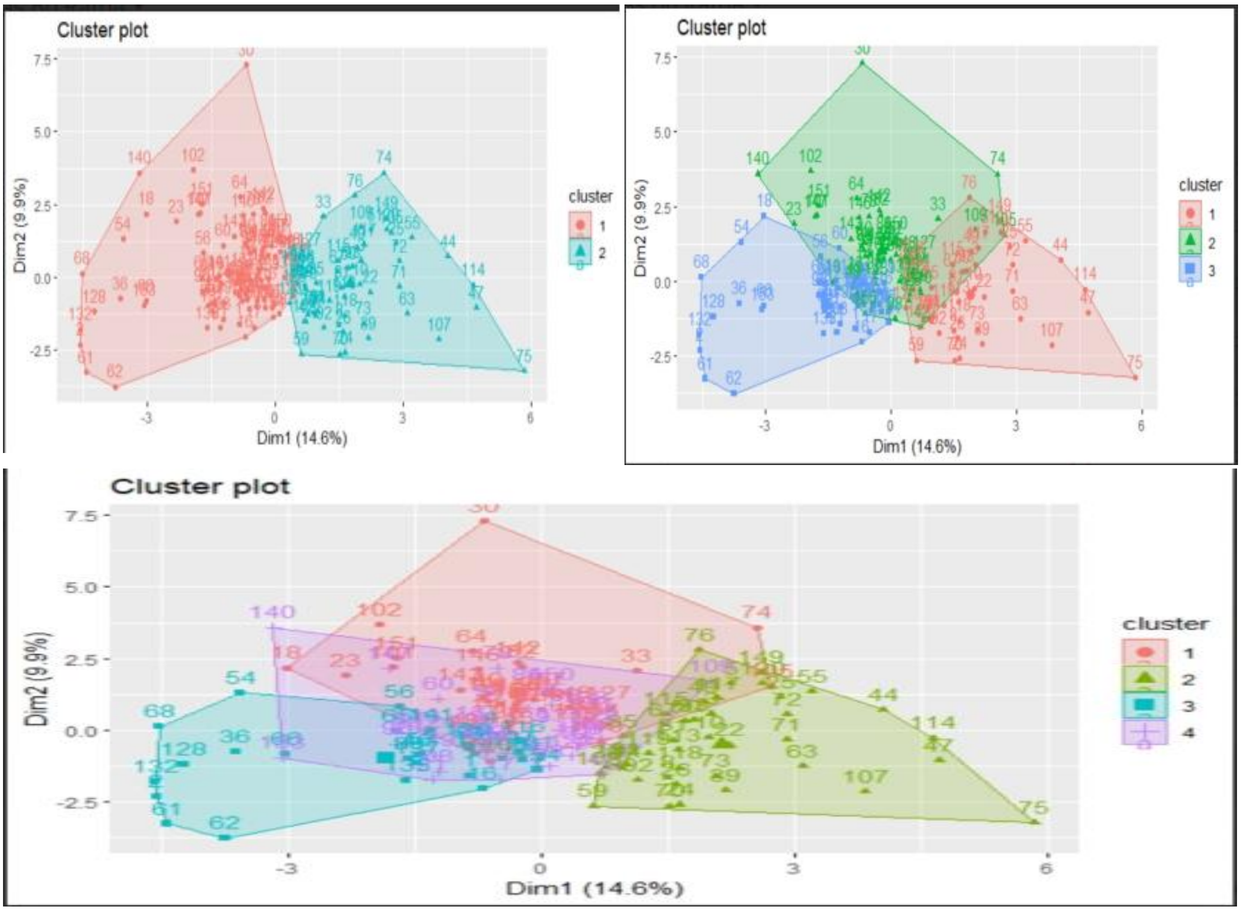


Figure 5 Cluster information

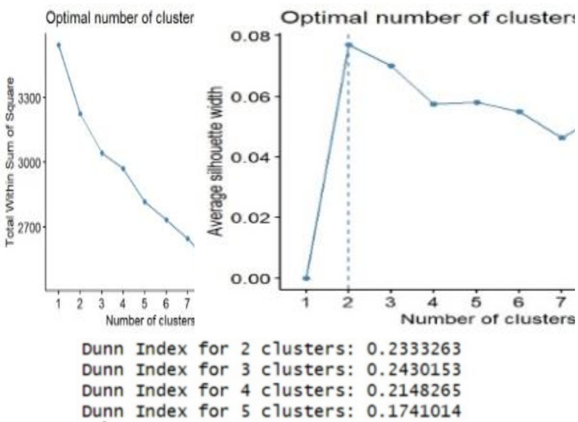


Figure 6 Optimal K-Value

The figure 6 shows the Dunn Index values for several clustering scenarios, ranging from 2 to 5 clusters. The Dunn Index is used to evaluate clustering quality by measuring both the separation between clusters and the compactness within each cluster. A higher Dunn Index value indicates better clustering performance. Based on the results displayed, the highest Dunn Index value is obtained when using 3 clusters (0.24), compared to 2 clusters (0.23), 4 clusters (0.22), and 5 clusters (0.17). This suggests that 3 clusters provide the most optimal grouping, as it achieves a better balance between clear separation among clusters and tight grouping of data points within each cluster. Therefore, using 3 clusters yields the most effective and meaningful clustering structure for the dataset.To ensure the best number of clusters to be selected, in the second step an internal validity test is carried out using the Connectivity, Silhouette, and Dunn indices. The smaller the Connectivity index and the larger the Silhouette and Dunn indices that are closer to 1 indicate the better the number of clusters obtained.

The identification of three distinct consumer clusters is consistent with recent findings in agro-industrial consumer behaviour research, which frequently observes segmentation patterns classified as: (1) highly involved consumers with strong product loyalty, (2) moderately involved consumers who exhibit price sensitivity, and (3) value-oriented consumers with lower brand attachment (Pradana & Maulani, 2023; Boito et al., 2021). In the context of processed chicken meat products, attributes such as halal certification, packaging quality, product freshness, and perceived safety were found to be critical determinants influencing consumer classification, aligning with existing literature on food product trust and certification-driven purchasing behavior (Yuliana, R., & Prasetyo, A. (2022).

The results of this clustering analysis provide strategically relevant insights for both policymakers and businesses. Cluster-based consumer segmentation enables micro, small, and medium-sized enterprises (MSMEs) to design differentiated marketing strategies, develop targeted product improvements, and refine pricing structures in accordance with the unique preferences of each consumer group (Anton et.al 2015). At the policy level, the findings support the design of non-uniform, tiered intervention strategies in the agroindustrial sector, which emphasize capability development, production enhancement, and market access tailored to the performance characteristics of each cluster (Martins & Pato, 2019). Therefore, the clustering framework presented in this study not only enhances the understanding of consumer perception dynamics but also contributes to the development of sustainable and context-specific regional agroindustry strategies.

4. CONCLUSIONS AND RECOMMENDATIONS

The factors in grouping based on consumer perception are Taste Variation, Price, Ease of obtaining products, availability, shape, packaging, safety and cleanliness, expiration date, promotion or discount, brand, net weight (quantity), product label and halal certification. Determining the optimal number of clusters and data partitioning using the K-Means method, based on evaluation using several clustering evaluation metrics such as the Elbow method, Silhouette Score, and Dunn Index. The use of K-Means Clustering can be very useful in grouping data based on similar features and finding the underlying structure in the data, the cluster variables formed are halal standardization and product price. Understanding consumer perception through clustering, companies can design more effective marketing strategies that are tailored to the needs and preferences of each consumer segment. Evaluation of the optimal number of clusters using various metrics and analysis of the characteristics of each cluster is very important to ensure that the strategy implemented is right on target and provides maximum results.

The findings of this study have significant policy implications for local governments, business support institutions, and stakeholders in the development of sustainable agro-industry. The approach to strengthening MSME competitiveness needs to be directed at cluster-based policies, rather than uniform policies. Local governments can design tiered intervention programs according to the characteristics and level of readiness of each cluster, for example by providing technology support and market access for superior clusters, innovation assistance and financing for medium-sized clusters, and empowerment and basic training for low-performing clusters. Furthermore, cross-actor synergy is needed between the government, universities, financial institutions, and the private sector to build an inclusive innovation ecosystem and value chain. Thus, agro-industry MSME development policies should not only focus on economic growth but also contribute to sustainable development by improving the welfare of business actors, preserving the environment, and strengthening local economic structures.

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REFERENCES

Andalib A ,Dinani H G , Mahmood Naderi Beni MN, (2023). Designing a paradigm of customer buying behavior affected by environmental sensory cues correspondent of sensory marketing rules Case study: ESFAHAN province coffee shops. Journal of Business Management Perspective | 22(55) , pp. 40-60 ISSN: 2645-4149. DOI: 10.48308/jbmp.2024.232132.1523

Banten Province. (2020). Regional Regulation of banten Province on Industrial Development Plan of Banten Province. November 16th, 2005. https://jdih.bantenprov.go.id/storage/places/peraturan/2022pd0036003_1702044792.pdf.

Boito, B., Lisbinski, E., Campo, M. D. M., Guerrero, A., Resconi, V., de Oliveira, T. E., & Barcellos, J. O. J. (2021). Perception of beef quality for Spanish and Brazilian consumers. *Meat Science*, *172*(April 2020), 108312. https://doi.org/10.1016/j.meatsci.2020.108312

Bristow, D. N., & Sebastian, R. J. (2001). Holy cow! Wait 'til next year! A closer look at the brand loyalty of Chicago Cubs baseball fans. *Journal of Consumer Marketing*, *18*(3), 256–273. https://doi.org/10.1108/07363760110392976

C.L. Martins, M.V. Pato (2019), Supply chain sustainability: A tertiary literature review, Journal of Cleaner Production, 225,995-1016, https://doi.org/10.1016/j.jclepro.2019.03.250

De Jonge, J., Frewer, L., Van Trijp, H., Jan Renes, R., de Wit, W., & Timmers, J. (2004). Monitoring consumer confidence in food safety: An exploratory study. In *British Food Journal* (Vol. 106, pp. 837–849). https://doi.org/10.1108/00070700410561423

Ekawati, R., & Yulis, N. (2013). *Klasifikasi Usaha Kecil dan Menengah (UKM) Sektor Industri Dengan Metode Fuzzy C-Means Clustering Wilayah Kota Cilegon. Seminar Nasional IENACO*, 1–7. ISSN: 2337-4349. https://www.academia.edu/download/47830430/jurnalnew6.pdf

Fathia, A. N., Rahmawati, R., & Tarno. (2016). *Analisis Klaster Kecamatan Di Kabupaten Semarang Berdasarkan Potensi Desa Menggunakan Metode Ward Dan Single Linkage. Jurnal Gaussian*, *5*(4), 801–810. DOI: https://doi.org/10.14710/j.gauss.5.4.801-810

Grunert, K. G. (2005). Food quality and safety: Consumer perception and demand. *European Review of Agricultural Economics*, *32*(3), 369–391. https://doi.org/10.1093/eurrag/jbi011

Kovacheva, M., Markovska, V., & Kulova, I. (2024). Price sensitivity of consumers to organic food and the most frequently purchased categories of organic food. *BIO Web of Conferences*, *102*. https://doi.org/10.1051/bioconf/202410204005

Martins, C. L., & Pato, M. V. (2019). Supply chain sustainability: A tertiary literature review. *Journal of Cleaner Production*, *225*,995–1016. https://doi.org/10.1016/j.jclepro.2019.03.250

Ministry of Industry. (2015). *National Industry Development Master Plan (RIPIN) 2015-2035*. https://kemenperin.go.id/ripin.pdf

Naini, N. F., Sugeng Santoso, Andriani, T. S., Claudia, U. G., & Nurfadillah. (2022). The Effect of Product Quality, Service

Quality, Customer Satisfaction on Customer Loyalty. *Journal of Consumer Sciences*, *7*(1), 34–50. https://doi.org/10.29244/jcs.7.1.34-50

Nusti D, Kanedi I, Rohmawan E. (2021) Application of K-Means Clustering Algorithm in Grouping Inventory Data at Putra Shop, Jurnal Komputer Informasi dan Teknologi.1 (1). 29-38. https://doi.org/10.53697/jkomitek.v1i1

Pradana, D. & Maulani, A. (2023) Quality Attribute Evaluation and Halal Awareness in Processed Meat Products, *Agroindustrial Technology Journal*, 7(2),101–109 DOI:10.32890/ijms2022.29.2.5

Rochmatulaili, E. (2020). The influence of food quality on consumer satisfaction inYoshinoya Royal Plaza Surabaya. *Proceeding 1 st International Conference on Business & Social Sciences (ICOBUSS)*. 405-416. DOI: 10.55299/ijec.v4i1.1296

Sabaté, J., & Soret, S. (2014). Sustainability of plant-based diets: Back to the future. *American Journal of Clinical Nutrition*, *100*(SUPPL.1). https://doi.org/10.3945/ajcn.113.071522

Sedera, R. M. H., Putra, R. Y., Saputra, E. K., & Ali, M. A. (2023). Organic Food: The Factors Influencing Consumers' Purchasing Intention. *Jurnal Manajemen Teori Dan Terapan | Journal of Theory and Applied Management*, *16*(2), 254–265. https://doi.org/10.20473/jmtt.v16i2.46107

Shan, L. C., De Brún, A., Henchion, M., Li, C., Murrin, C., Monahan, F. J., & Monahan, F. (2017). Consumer evaluations of processed meat products reformulated to be healthier – A conjoint analysis study (Vol. 1). doi:0.1016/j.meatsci.2017.04.239. Epub 2017 May 1.

Setyawan Agus Anton A A, Muzakan I, Muhammad F W , Syamsudin, Sidiq N P. (2015). *Journal of Competitiveness*, 7(2),60-74, DOI:10.7441/joc. 2015. 02. 04.

Suhaeni, C., Kurnia, A., & Ristiyanti, R. (2018). Perbandingan Hasil Pengelompokan menggunakan Analisis Cluster Berhirarki, K-Means Cluster, dan Cluster Ensemble (Studi Kasus Data Indikator Pelayanan Kesehatan Ibu Hamil). *Jurnal Media Infotama*, *14*(1). https://doi.org/10.37676/jmi.v14i1.469

Trenggonowati, D. L., Ulfah, M., Ekawati, R., & Yusuf, V. A. (2019). Organization clustering airports using K-Means clustering algorithm. *IOP Conference Series: Materials Science and Engineering*, *673*(1). https://doi.org/10.1088/1757899X/673/1/012081