

AI-Driven Customers Segmentation Using K-Means Clustering

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Article Information	ABSTRACT
Article History Received : December 18, 2024 Revised : December 30, 2024 Published : January 10, 2025	Effective customer segmentation is essential for businesses to enhance marketing strategies and improve customer engagement. This study applies K-Means clustering to segment customers based on demographic and behavioral data collected through structured surveys and questionnaires. The dataset includes attributes such as age, income, purchase frequency, product preferences, and brand loyalty. Data preprocessing involved normalization, imputation, and encoding to ensure quality and suitability for clustering. The optimal number of clusters was determined using the Elbow Method and Davies-Bouldin Index, resulting in three distinct segments: High-Spending, Frequent Shoppers, Price-Sensitive, Infrequent Shoppers, and Brand-Loyal, Moderate Shoppers. These clusters provide actionable insights for businesses, enabling tailored strategies such as loyalty programs, discounts, and targeted promotions. The Davies-Bouldin Index score of 1.27 and visualization using Principal Component Analysis (PCA) validated the effectiveness and distinctiveness of the segmentation. This research highlights the potential of AI-driven methods like K-Means clustering in uncovering hidden patterns in customer behavior, offering a robust alternative to traditional segmentation approaches. Future studies could explore larger datasets, integrate additional behavioral attributes, and compare the performance of other clustering algorithms to further enhance segmentation outcomes.
Keywords: <i>AI-driven segmentation;</i> <i>Behavioural analysis;</i> <i>Customer segmentation;</i> <i>K-Means clustering;</i> <i>Market segmentation.</i>	

INTRODUCTION

In today's fast-paced and data-driven business environment, understanding customer behaviour is crucial for businesses to stay competitive and achieve sustained success (Sudirjo, 2023). Strategic market segmentation involves breaking down a large customer base into smaller, unique groups based on common characteristics, plays a pivotal role in helping businesses craft tailored marketing strategies (Hafez, 2024; Tarek & Hossam, 2022). Traditional segmentation methods, which primarily rely on demographic and psychographic data, often fall short in capturing the complexity of customer behaviours, especially with the growing volume and diversity of data now available. As a result, businesses face increasing challenges in gaining actionable insights from traditional segmentation approaches (Adesoga et al., 2024; Fischer, 2024; Hariguna, 2024).

With the explosion of data and the increasing sophistication of analytical tools, businesses are turning to advanced methodologies to obtain a more comprehensive understanding of their customers (Adewusi et al., 2024). Artificial intelligence (AI) and machine learning (ML) have proven to be highly effective tools for advancing the practice of market segmentation (Mandapuram et al., 2020; Rane et al., 2024). These technologies enable businesses to analyse

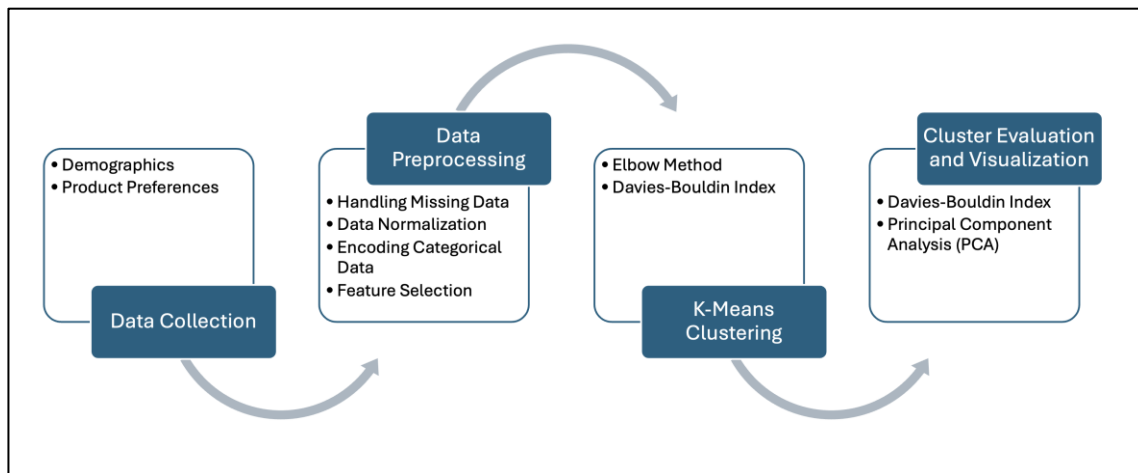
large and complex datasets more efficiently, uncover hidden patterns, and create more accurate customer profiles (Bharadiya, 2023). K-Means clustering, a popular unsupervised machine learning algorithm, is frequently employed in market segmentation to organize data into clusters by identifying patterns and similarities in customer behavior and preferences, all without relying on predefined labels (Kalusivalingam et al., 2020; Lone & Warale, 2022; Niloy et al., 2024). Identifying customer segments based on purchasing behavior, brand loyalty, and engagement levels enables businesses to craft more effective and targeted marketing strategies (Adeniran et al., 2024; Rane et al., 2023).

Recent research has shown the growing application of K-Means clustering across various industries such as retail, e-commerce, and finance, where customer data is both abundant and multifaceted. The algorithm's ability to identify meaningful customer segments helps businesses tailor their offerings and optimize customer experiences (Ayodele & Sodeinde, 2024; Chaudhary et al., 2024; Tabianan et al., 2022). However, while many studies have demonstrated the efficacy of AI-driven segmentation in these sectors, there is limited research focused on the practical application of K-Means clustering in a context where customer data is derived from structured surveys and questionnaires, and where specific behavioural insights can directly inform business decisions (Ahmed et al., 2020).

The primary objective of this study is to apply K-Means clustering to a dataset obtained through customer surveys and questionnaires to segment the customer base according to their demographic profiles and purchasing behaviours. The survey collects key data points such as age, gender, location, product preferences, and purchasing frequency. This approach aims to uncover distinct customer segments that will enable businesses to better understand their target audience and develop customized marketing campaigns. By focusing on actionable insights derived from the clustering analysis, this research intends to show how AI-driven segmentation can be applied to optimize customer targeting and ultimately enhance business decision-making. This study aims to bridge the gap in existing research by offering a detailed and practical application of K-Means clustering for market segmentation in real-world context, demonstrating how AI tools can improve customer segmentation processes and contribute to business success.

RESEARCH METHODS

To achieve the objectives of this study, a systematic approach was employed to collect and analyse customer data. The primary method for gathering relevant data was through a structured survey and questionnaire, designed to capture key demographic and behavioural insights. By using customer data, the study aimed to uncover hidden patterns in purchasing behaviour and segment the customer base accordingly. The analysis utilized the K-Means Clustering algorithm, a well-known unsupervised machine learning method that organizes data into groups based on similarities, allowing for the identification of distinct customer segments. This section outlines the data collection process, data preprocessing steps, and the application of K-Means clustering to identify meaningful customer segments.

**Figure 1.** Research Methods

Data Collection

Data for this research was obtained through a structured survey and questionnaire distributed to a target group of customers. The survey aimed to capture both demographic and behavioural data, which are essential for understanding the factors that influence customer purchasing decisions. The data collection process utilized a set of survey questions designed to gather relevant information, as detailed in Tabel 1.

Tabel 1. Survey Questions

No	Questions	Answer Type	Options
Demographics Parameter			
1	What is your age group?	Multiple Choice	Below 18; 18–24; 25–34; 35–44; 45–54; 55+
2	What is your gender?	Multiple Choice	Male; Female; Other
3	What is your average spending per purchase?	Multiple Choice	Less than Rp100,000; Rp100,000–Rp500,000; Rp501,000–Rp1,000,000; More than Rp1,000,000
4	What is your current place?	Multiple Choice	Bandung; Cimahi; Garut; Bogor; Other
Product Preferences			
5	Which category of products do you purchase most frequently?	Multiple Choice	Snacks; Frozen Food; Cake & Pastries; Fresh Produce; Other
6	How often do you purchase products?	Multiple Choice	Daily; Weekly; Monthly; Occasionally
7	How satisfied are you with the quality of the products?	Likert Scale (1–5)	1 = Strongly Dissatisfied; 2 = Dissatisfied; 3 = Neutral; 4 = Satisfied; 5 = Highly Satisfied
8	How important are discounts or promotions in your purchasing decisions?	Likert Scale (1–5)	1 = Not Important, 2 = Slightly Important, 3 = Neutral, 4 = Important, 5 = Very Important

In total, 500 valid responses were collected from a wide variety of customers representing different demographics, locations, and interests. This rich dataset provided a robust foundation for clustering analysis.

Data Preprocessing

Before applying K-Means clustering, the collected data underwent several preprocessing steps to ensure the quality and suitability for clustering:

1. **Handling Missing Data:** Missing values in the dataset were handled through imputation methods. For numerical variables, the missing values were replaced with the mean of the corresponding column, while for categorical variables, the mode (most frequent category) was used (Raja & Thangavel, 2020).
2. **Data Normalization:** Given that K-Means clustering is influenced by the scale of the data, it was essential to normalize the numerical variables. Standardization was performed to convert the data into a standard normal distribution, ensuring that each feature had an equal impact on the clustering process (Huang et al., 2021).

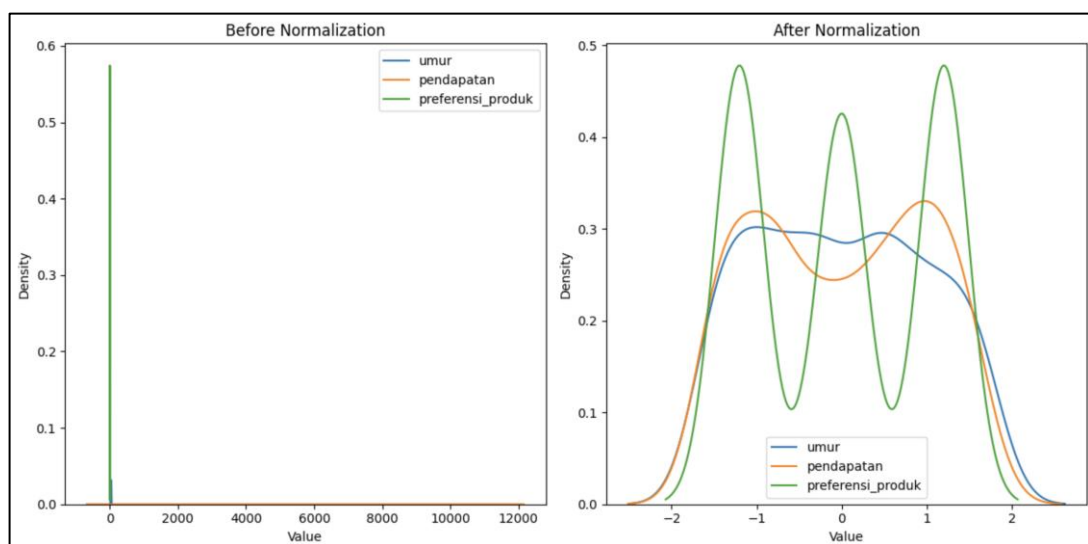


Figure 2. Data Normalization

3. **Encoding Categorical Data:** The survey included categorical variables (e.g., gender, product preferences). These variables were converted into numerical values using One-Hot Encoding, which creates binary variables (0 or 1) to represent the different categories of each attribute (Andreswari et al., 2023).
4. **Feature Selection:** Only relevant features that could provide insights into customer behaviour were retained. Features with low variance or insignificant impact on clustering were excluded to reduce noise and improve the model's performance (Ahmed et al., 2020).

K-Means Clustering

The K-Means Clustering algorithm was used to group the customers into distinct segments based on similarities in their responses. This unsupervised learning technique does not require labelled data and identifies clusters by minimizing the within-cluster sum of squared distances (Kalusivalingam et al., 2020; Lone & Warale, 2022; Nasution et al., 2023). The primary steps in the K-Means algorithm are:

1. **Initialization:** K initial cluster centroids are randomly chosen from the dataset.
2. **Assignment Step:** Each data point (customer) is assigned to the closest centroid based on the Euclidean distance.

3. Update Step: The centroids are updated by calculating the mean of all the points assigned to each cluster.
4. Repeat: Steps 2 and 3 are repeated iteratively until the centroids stabilize or converge.

The Elbow Method was used to identify the optimal number of clusters (K). The Sum of Squared Errors (SSE) was plotted for different values of K, and the "elbow" point, where the SSE starts to level off, indicates the ideal number of clusters. (Darmawan et al., 2024; Hamka & Ramdhoni, 2022). Figure 3 illustrates the final optimal cluster determined using the Elbow method.

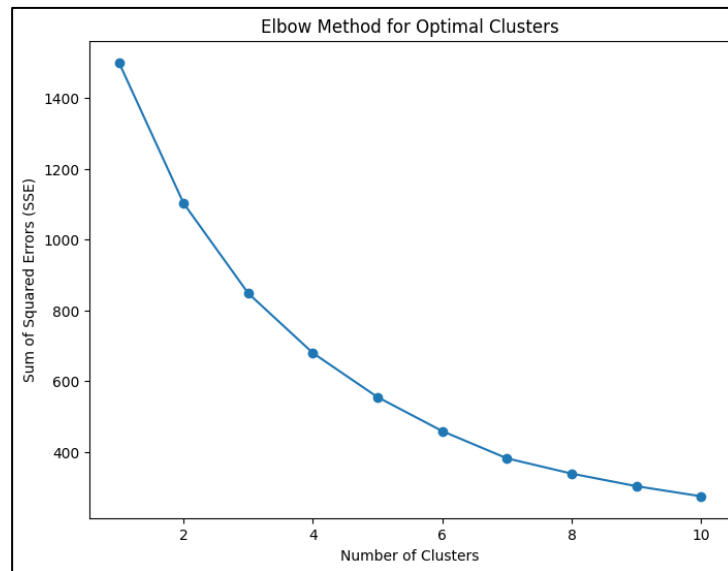


Figure 3. Elbow Optimal Clustering

Cluster Evaluation and Visualization

To evaluate the effectiveness of the clusters, the following techniques were used:

1. **Davies-Bouldin Index:** This index calculates the average similarity ratio of each cluster with the cluster that is most like it. A lower Davies-Bouldin Index indicates that the clusters are more separated and well-defined (Ros et al., 2023).
2. **Principal Component Analysis (PCA):** PCA was used to reduce the data's dimensionality and visualize the clusters in two dimensions. This approach aids in visually verifying whether the clusters are well-separated in the feature space. By transforming the data into two components, PCA facilitates the identification of distinct customer segments based on the clustering results (Abdulhafedh, 2021; Bandyopadhyay et al., 2021). Figure 4 shows the market segmentation with K-Means using PCA Visualization.

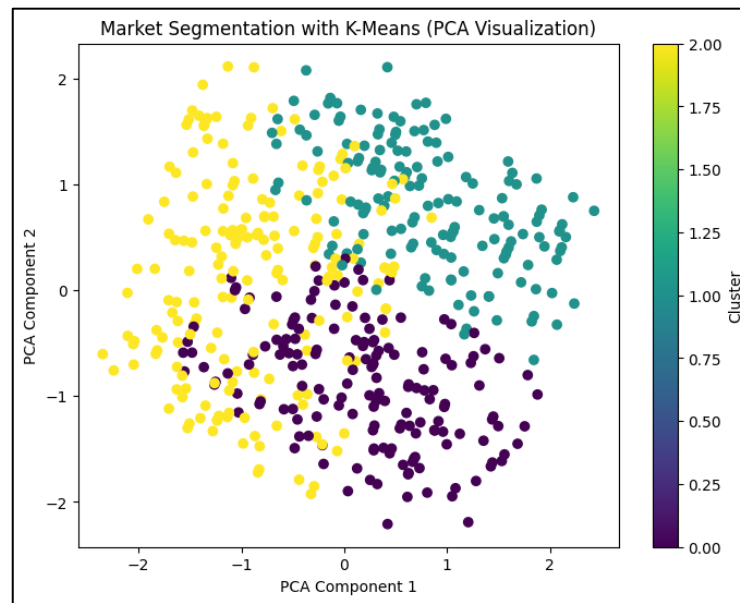


Figure 4. Visualization of the customer segments with the PCA method

The PCA method's visualization of customer segments offers a clear depiction of the clusters created by the K-Means algorithm in a two-dimensional space. By reducing the high-dimensional data into two principal components, the PCA plot highlights the distinctiveness of each segment while preserving the maximum variance in the dataset. Each cluster is color-coded to represent a specific customer group, illustrating their separation and cohesion. This clear visualization shows that the clustering process effectively grouped similar customers based on shared characteristics, while preserving a distinct separation between different segments. This is crucial for developing targeted marketing strategies and deriving actionable insights.

RESULTS AND DISCUSSION

Results of Data Analysis

The data analysis was conducted using K-Means Clustering to categorize the customer base into separate groups based on their survey responses. Following data preprocessing and determining the optimal number of clusters through the Elbow Method and Davies-Bouldin Index, the analysis identified three distinct customer segments. These segments are defined based on the key characteristics of the respondents, which include purchasing behaviour, preferences, and demographic traits. The following Tabel 2 summarizes the characteristics of each segment.

Tabel 2. Customer Segmentation

Segment	Key Characteristics	Size (%)
Segment 1: High-Spending, Frequent Shoppers	Customers who frequently make purchases and demonstrate high spending patterns. Loyal to premium brands.	35%
Segment 2: Price-Sensitive, Infrequent Shoppers	Customers who are highly price-sensitive and make infrequent purchases, primarily driven by discounts.	40%
Segment 3: Brand-Loyal, Moderate Shoppers	Customers who display moderate purchasing behaviour, are loyal to specific brands, and prioritize quality.	25%

These segments were derived based on the clustering process and represent different customer profiles, each with unique preferences and behaviours. The Davies-Bouldin Index for the clusters was calculated to measure the quality of the clustering. The results showed a Davies-Bouldin Index of 1.27, which indicates that the clusters are reasonably well-separated, with customers within each cluster being more similar to each other than to those in other clusters. Furthermore, the application of Principal Component Analysis (PCA) provided a two-dimensional visualization of the customer segments. This visualization confirmed that the clusters were distinct, as evidenced by the clear separation between the different groups in the reduced feature space.

Discussion

The results of this study align with previous research that has highlighted the importance of segmenting customers to create personalized marketing strategies. Studies have shown that segmenting customers based on purchasing behaviour and preferences leads to improved targeting, higher customer satisfaction, and increased sales (Smith, 2024). Techniques like K-Means clustering effectively identify distinct customer groups, enabling businesses to tailor strategies and optimize marketing efforts (Ayodele & Sodeinde, 2024). However, this study's findings also reveal some contrasts with prior research. For instance, while previous studies often segment customers based on basic demographic characteristics (age, gender, income), our research shows that behavioural attributes such as purchase frequency and brand loyalty are stronger predictors for segmenting customers. This implies that businesses should consider not only traditional demographic data but also more dynamic behavioural factors to gain a better understanding of customer preferences.

The High-Spending, Frequent Shoppers segment in this study reflects a common finding in retail segmentation, where loyal customers who spend more represent a key target for exclusive offers and personalized services. The Price-Sensitive, Infrequent Shoppers, however, offer a unique insight into a group that may require price-based incentives to encourage more frequent purchasing, which aligns with findings from Miller et al. who highlighted the impact of discounts on this customer type (Miller et al., 2021). On the other hand, the Occasional Shoppers, Low Engagement segment presents a challenge, as these customers show low levels of brand loyalty and engagement. This segment may require more targeted re-engagement strategies, such as loyalty programs or personalized marketing campaigns that encourage greater interaction with the brand (Sampathrajan et al., 2023). This is in line with previous research which indicated that customer re-engagement efforts are particularly crucial for segments with low brand interaction (Vatavwala et al., 2022).

The results of this study offer businesses actionable insights to optimize their marketing strategies by tailoring approaches to different customer segments. Price-Sensitive, Infrequent Shoppers can be encouraged to purchase more frequently through limited-time promotions and discounts, while Brand-Loyal, Moderate Shoppers can be engaged with product bundles or loyalty rewards to enhance their retention. For High-Spending, Frequent Shoppers, exclusive product offerings or VIP services can be effective in maintaining their loyalty and increasing satisfaction. Additionally, Occasional Shoppers can be targeted with re-engagement campaigns or personalized product recommendations to reignite their interest and drive conversions.

CONCLUSION

This study aimed to apply K-Means clustering to segment customers based on survey and questionnaire data, providing businesses with actionable insights for targeted marketing and enhanced customer engagement. The clustering analysis results identified three distinct customer segments, each defined by different purchasing behaviors, product preferences, and engagement levels: High-Spending, Frequent Shoppers; Price-Sensitive, Infrequent Shoppers; and Brand-

Loyal, Moderate Shoppers. These segments provide meaningful customer profiles that businesses can use to optimize their marketing strategies.

The analysis confirmed the effectiveness of K-Means clustering for segmenting customer data. With a Davies-Bouldin Index of 1.27, indicating well-separated clusters, and the use of Principal Component Analysis (PCA) for visualization, the results validated the quality of the segmentation. These findings suggest that businesses can move beyond traditional demographic-based segmentation, incorporating behavioral attributes such as purchase frequency, brand loyalty, and engagement levels, for more effective targeting. Based on these results, businesses can implement practical strategies to engage different customer segments effectively. For Price-Sensitive, Infrequent Shoppers, targeted discounts or limited-time promotions can encourage higher purchase frequency. For Brand-Loyal, Moderate Shoppers, loyalty programs or exclusive offers can strengthen engagement and retention. Meanwhile, High-Spending, Frequent Shoppers can be further incentivized through VIP programs or personalized premium product offerings to enhance their experience and maintain their loyalty.

From a theoretical perspective, this study highlights the importance of integrating both demographic and behavioral data for more comprehensive market segmentation. It demonstrates the power of AI-driven segmentation, particularly K-Means clustering, in uncovering deeper insights into customer behaviors that traditional methods may overlook. Future research could enhance segmentation models by incorporating additional data sources such as transaction history, social media activity, or psychographic data, allowing for even more personalized marketing strategies. Further studies could also explore the application of clustering techniques to larger datasets from various industries, comparing K-Means clustering with other unsupervised learning algorithms, such as DBSCAN or Hierarchical Clustering, to assess the robustness and adaptability of these techniques across different market contexts. Furthermore, examining how customer behavior evolves over time could offer deeper insights into segmentation trends and guide long-term business strategies.

In conclusion, this research underscores the value of AI-driven customer segmentation methods, providing businesses with actionable recommendations to optimize their marketing efforts. The findings contribute to the growing body of knowledge on machine learning applications in marketing and customer behavior analysis, offering a foundation for future research and practical business applications.

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