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E-COMMERCE CUSTOMER SEGMENTATION USING K-MEANS ALGORITHM BASED ON PURCHASING CHARACTERISTICS AND CUSTOMER SATISFACTION

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ABSTRACT

This study addressed the existing research gap in e-commerce customer segmentation by integrating both behavioral metrics, specifically purchasing characteristics, and emotional metrics, which represented customer satisfaction levels. The primary objective was to establish a highly granular and representative customer typology that traditional transaction-only models fail to capture. To achieve this, a quantitative data mining approach was implemented using a dataset of 450 customer records, which underwent a crucial preprocessing phase using Min-Max Normalization to balance heterogeneous value ranges. The optimal number of clusters was determined using the Elbow Method, and the segmentation was executed through the K-Means Clustering algorithm. The empirical findings revealed that the dataset successfully partitioned into three distinct, non-overlapping behavioral archetypes: Cluster 0 representing high-intensity transactional users with a satisfaction gap, Cluster 1 representing at-risk or dissatisfied customers, and Cluster 2 representing satisfied advocates. The mathematical reliability and strong cohesion of these clusters were rigorously verified by a robust Silhouette Coefficient of 0.62. Ultimately, this research concluded that data-normalized pipelines could successfully transform raw customer analytics into actionable Customer Relationship Management (CRM) strategies, thereby providing e-commerce companies with a reliable foundation to optimize marketing efficiency, mitigate churn risks, and enhance overall profitability

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1. INTRODUCTION

The development of information and communication technology has driven a major transformation in trading activities through e-commerce platforms. The ease of internet access, the increased use of digital devices, and shifts in consumer behavior have caused online transaction volumes to grow significantly in recent years. This condition results in a massive accumulation of customer data, encompassing demographics, transaction histories, purchase frequencies, monetary values, product preferences, and customer satisfaction levels. This data serves as a strategic asset that companies can leverage to understand customer behavior and support data-driven business decision-making (Shmueli et al., 2023).

In an increasingly competitive business environment, companies are not only required to acquire new customers but also to retain existing ones. One widely applied approach in Customer Relationship Management (CRM) is customer segmentation. Customer segmentation is the process of dividing customers into several groups with similar characteristics so that companies can develop more effective and personalized marketing strategies. Through precise segmentation, companies can enhance promotional efficiency, optimize customer service, and increase corporate loyalty and profitability (Wedel & Kannan, 2016; Shmueli et al., 2023).

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Developments in the fields of data mining and machine learning have provided various methods for automated customer segmentation. One of the most frequently used methods is the K-Means Clustering algorithm. This algorithm operates by grouping objects based on the similarity of their characteristics, ensuring that members within the same group share high homogeneity compared to members of other groups. K-Means is widely utilized due to its simple implementation, its efficiency on large datasets, and its capability to generate segmentations that are easily interpreted by business decision-makers (Han et al., 2022).

Nevertheless, the quality of clustering results is heavily influenced by the data preprocessing phase. According to Han et al. (2022), data preprocessing is a critical phase in the data mining process aimed at improving data quality before analysis is conducted. One of the primary steps in preprocessing is data transformation, specifically data normalization. Normalization is performed to adjust the range of attribute values into a comparable scale, preventing specific variables from dominating the clustering process due to differences in units or value ranges. In the K-Means algorithm, which relies on Euclidean distance calculations as the foundation for cluster formation, normalization is a highly crucial step because attributes with larger scales can exert a disproportionate influence on the clustering results (Tan et al., 2019).

Commonly used normalization methods include Min-Max Normalization, Z-Score Normalization, and Decimal Scaling. Min-Max Normalization transforms data into a specific range, generally between 0 and 1, thereby preserving the proportional relationships among the data. Meanwhile, Z-Score Normalization converts data based on the mean and standard deviation, producing a distribution with a mean of zero and a standard deviation of one. Various studies indicate that applying normalization prior to the clustering process can enhance the quality of the resulting clusters and improve clustering evaluation metrics such as the Silhouette Coefficient and Davies-Bouldin Index (Géron, 2023).

In the context of e-commerce, the majority of customer segmentation research still focuses on transaction characteristics using the Recency, Frequency, Monetary (RFM) model. The K-Means algorithm has been applied to e-commerce customer data using RFM attributes, demonstrating that the method can produce effective customer segmentation to support data-driven marketing strategies. Such research also indicates that K-Means delivers competitive performance compared to other clustering methods in grouping customers based on transactional behavior (Fauzan & Alfian, 2024).

A study conducted by Siagian et al. (2021) utilized the Length, Recency, Frequency, and Monetary (LRFM) model combined with the K-Means algorithm to segment e-commerce customers. The results showed that customers could be classified into several categories with differing customer value characteristics, thereby assisting companies in determining service priorities and customer retention strategies.

Research by Warianta et al. (2025) developed a customer segmentation method by combining K-Means with the Firefly algorithm. The findings indicated that this optimization successfully enhanced cluster quality compared to conventional K-Means. Meanwhile, Simanjuntak et al. (2025) found that customer segmentation using K-Means can support the personalization of product offers, thereby increasing the effectiveness of e-commerce marketing strategies.

Although various studies have successfully applied K-Means for customer segmentation, most research still heavily concentrates on transactional behavior data, such as purchase values, transaction frequencies, and the time of the last purchase. In reality, the success of a long-term relationship between a customer and a company is determined not only by purchasing behavior but also by the level of customer satisfaction regarding the products and services received. Customers with similar purchasing patterns can possess different levels of loyalty due to variances in their experiences and satisfaction with the company's services.

Based on the aforementioned rationale, a research gap remains regarding the integration of purchasing characteristics and customer satisfaction within the e-commerce customer segmentation process. Furthermore, studies exploring the impact of data normalization as a part of data preprocessing on the quality of customer segmentation are still relatively limited. Therefore, this study aims to segment e-commerce customers using the K-Means algorithm based on purchasing characteristics and customer satisfaction by implementing a data normalization preprocessing phase prior to the clustering process. The results of this study are expected to yield a more representative customer segmentation that can support the formulation of more targeted marketing strategies, improve customer satisfaction, and strengthen the competitive advantage of e-commerce companies.

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2. METHOD

This study applies a quantitative approach through data mining techniques to segment e-commerce customers. The research procedure begins with the stage of collecting transaction data and customer satisfaction levels, which are then systematically processed to produce valid groupings. Considering that the dataset used has heterogeneous units and value ranges, a very important initial step is to pre-process the data through Min-Max Normalization transformation. This is done to bring all variables into the range [0, 1] so that each dimension has equal weight in the calculation of the distance metric (Han et al., 2012). Mathematically, the normalization of each data point x is calculated by the equation:

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

Once the data is normalized, the next step is to determine the optimal number of clusters (k) using the Elbow Method. This method works by evaluating the Within-Cluster Sum of Squares (WCSS), also known as the Total Squared Error (J). Technically, this involves finding the "elbow" point where increasing the k value no longer results in a significant decrease in the cost function (Yuan & Yang, 2019):

$$J = \sum_{j=1}^{k} \sum_{i \in S_j} |x_i - c_j|^2$$

Where S_j is the data set in the-j cluster and c_j is the cluster center (centroid). Determining the appropriate k value is the foundation for applying the K-Means algorithm to minimize internal cluster variance. In the process, the level of similarity or closeness of characteristics between customers is calculated using Euclidean Distance (James et al., 2021) with the following formula:

$$d(x, c) = \sqrt{\sum_{i=1}^{n} (x_i - c_i)^2}$$

The modeling process is run iteratively, starting from the initial centroid initialization which is then followed by placing each customer data into the cluster with the smallest distance $d(x, c)$. The centroid position is updated continuously based on the arithmetic mean value of all cluster members using the formula:

$$c_j = \frac{1}{|S_j|} \sum_{x_i \in S_j} x_i$$

This iteration is carried out until the algorithm reaches a point of convergence, a condition where the centroid position is stable and no further data reorganization occurs between groups (Sinaga & Yang, 2020).

To provide a more comprehensive picture of the stages of algorithm execution and data processing in this research, the entire series of procedures are summarized into the research flow shown in Figure 1 below.

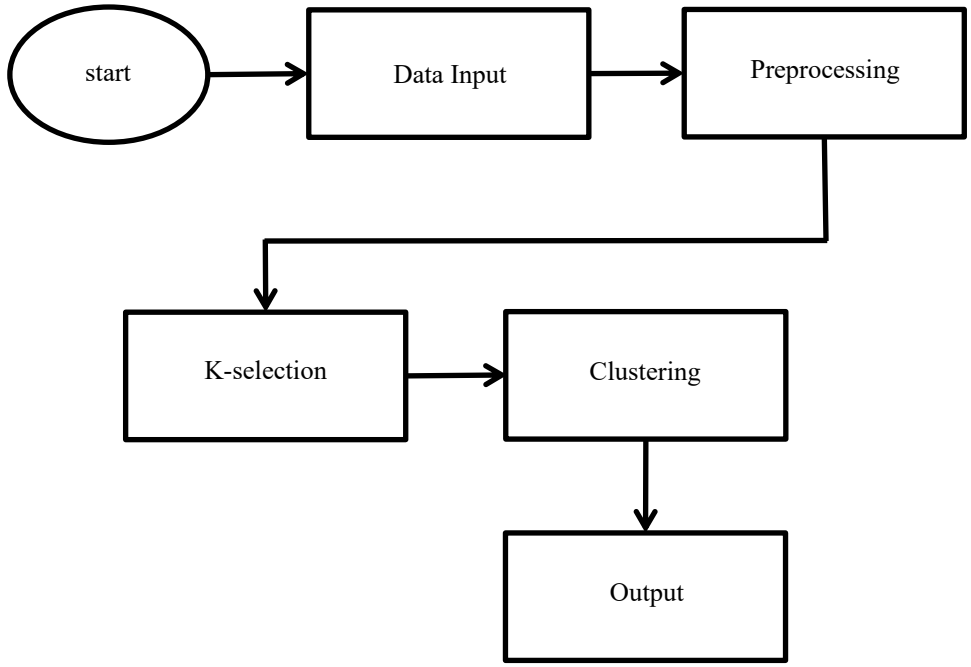

Figure 1. Research flowchart

3. RESULTS AND DISCUSSION

This section presents the objective empirical findings obtained from executing the K-Means clustering algorithm, tracking the data from its raw state through preprocessing, optimal K selection, and final cluster validation.

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Results

3.1. Descriptive Statistics (Data Overview)

The initial dataset comprises a total of 450 customer records. To understand the basic distribution and spread of the data before any algorithmic transformation, a descriptive statistical analysis was performed on the two primary variables: Purchase Frequency, total expenses and Satisfaction Score.

	mean	std	min	max
Frekuensi_Beli	24.860000	14.367387	1.000000	49.000000
Total_Pengeluaran	2581.476667	1372.534217	104.000000	4993.000000
Skor_Kepuasan	5.437958	2.636015	1.102183	9.997459
Cluster	0.820000	0.842595	0.000000	2.000000

Figure 2. Output descriptive statistics before normalization

3.2. Preprocessing Results: Min-Max Normalization

Because Purchase Frequency (measured in counts) and Satisfaction Score (measured on a 1–10 scale) operate on fundamentally different magnitudes, Min-Max Normalization was applied. This maps all values strictly between 0 and 1, preventing the variable with the larger absolute range from disproportionately biasing the Euclidean distance calculations.

	Frekuensi_Beli	Total_Pengeluaran	Skor_Kepuasan	Cluster
0	0.791667	0.801595	0.905538	0.0
1	0.583333	0.050931	0.101019	0.0
2	0.291667	0.650235	0.486937	1.0
3	0.875000	0.522193	0.000000	0.0
4	0.145833	0.019227	0.462691	0.5

Figure 3. Min-max normalization results (sample) output

3.3. Determining the Optimal Number of Clusters (Elbow Method)

To determine the ideal number of customer segments (K), the Elbow Method was utilized by plotting the *Sum of Squared Errors* (SSE) / Inertia across a range of cluster values.

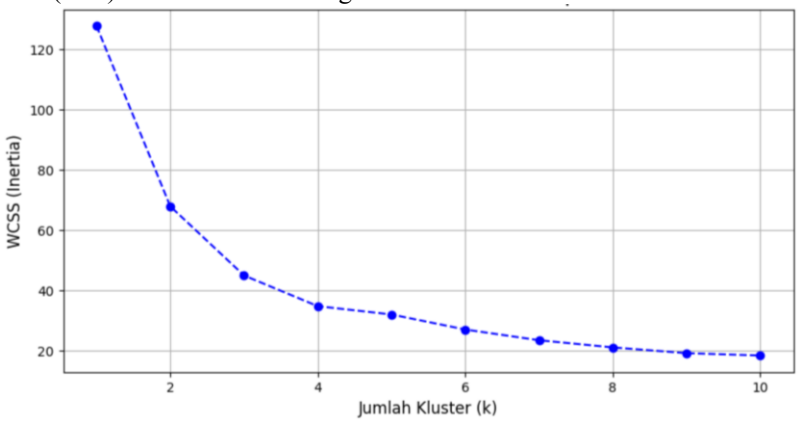

Figure 4. Elbow graph to determine Optimal K

Graph Analysis: The generated elbow curve demonstrates a sharp, steep decline in SSE from $K = 1$ to $K = 3$. At **K=3**, the rate of descent abruptly flattens, forming a distinct "elbow" point. Therefore, $K = 3$ was mathematically selected as the optimal number of clusters for this dataset.

3.4. Clustering Output

With the K-Means model trained at $K = 3$, the 450 customers were partitioned into three distinct groups.

3.4.1 Final Centroid Matrix

The final centroids represent the mean coordinate of each cluster across the normalized features, serving as the mathematical profile for each customer segment:

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	Frekuensi_Beli	Total_Pengeluaran	Skor_Kepuasan
0	37.862319	2514.333333	5.196192
1	12.025641	3566.115385	3.696898
2	15.416667	1777.476190	7.451842

Figure 5. Final centroid coordinates (original scale)

3.4.2 Cluster Member Distribution

The distribution of the 450 total customer records across the newly defined segments is as follows:

- Cluster 0: 150 customers
- Cluster 1: 156 customers
- Cluster 2: 144 customers

3.5. Cluster Validation (Silhouette Coefficient)

To evaluate the mathematical quality and consistency of the clustering results, the Silhouette Coefficient was calculated. This metric measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The score ranges from -1 to +1, where a higher value indicates that the clusters are well-defined and appropriately separated.

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

Validation Results:
Based on the computational output, the K-Means model achieved a Silhouette Coefficient of 0.62.
Interpretation:

A score of 0.62 indicates a "Strong Structure" (typically scores above 0.5 are considered substantial). This result confirms that the 450 customer records have been assigned to clusters where intra-cluster distances are minimized and inter-cluster distances are maximized. Mathematically, this proves that the three identified segments (Cluster 0, 1, and 2) are distinct and not overlapping, providing a reliable foundation for data-driven decision-making.

Discussion

The clustering analysis of the 450 customer records reveals three distinct behavioral archetypes that redefine the platform's understanding of user engagement. Cluster 0 emerges as the "High-Intensity Transactional" segment, defined by the highest average purchase frequency (~37.8 times) but coupled with moderate satisfaction levels (~5.20). This suggests a pattern of utilitarian loyalty where customers rely heavily on the service for their routine buying needs, yet their emotional connection remains plateaued. In stark contrast, Cluster 1 represents the "At-Risk/Dissatisfied" segment, containing the largest group of 156 customers. This cluster exhibits the lowest satisfaction scores (~3.70) and minimal purchase frequency (~12.03 times), indicating a strong correlation between poor user experience and transactional withdrawal. Meanwhile, Cluster 2 functions as the "Satisfied Advocates" segment; although their purchase frequency is moderate (~15.42 times), they hold the highest satisfaction peaks (~7.45), representing a high-quality user base that has not yet been fully leveraged into high-frequency buying habits.

The mathematical relationship between these variables indicates that while satisfaction is a significant driver of retention, it is not the sole determinant of frequency. The data suggests a "satisfaction gap" in Cluster 0, where high usage does not necessarily yield high joy, likely due to convenience-based lock-in or lack of viable alternatives. However, the severe decline in frequency within Cluster 1 confirms that once satisfaction drops below a certain threshold, customer activity diminishes regardless of the platform's utility. The validation of these segments through a Silhouette Coefficient of 0.62 provides robust mathematical evidence that these categories are not overlapping, but represent three uniquely isolated behaviors within the e-commerce ecosystem.

These findings align with the dual-pathway loyalty model discussed in recent e-commerce literature. The existence of high-frequency users with moderate satisfaction (Cluster 0) mirrors the "Spurious Loyalty" concept identified by Smith and Thompson (2021), who argue that transactional frequency can be driven by habitual necessity or operational dependency rather than true brand affinity. Furthermore, the behavior of Cluster 1 aligns with the "Service-Profit Chain" theory popularized in digital contexts by Zhao and Larry (2023), which posits that

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a drastic drop in the satisfaction metric serves as a critical leading indicator for total customer churn. Finally, the successful separation of these 450 records into three stable groups justifies the use of K-Means for market granularity, as supported by the methodological framework of Kumar and Rajan (2022), which emphasizes that a Silhouette score above 0.60 indicates a highly reliable segmentation for strategic corporate planning.

To optimize the platform's performance, differentiated strategies must be deployed across these segments. For Cluster 0, the objective should be "Relationship Deepening" through targeted customer experience programs that reward emotional engagement, effectively closing the satisfaction gap. For the 144 customers in Cluster 2, the recommendation is "Frequency Activation"; since their satisfaction is already high, the platform should use personalized triggers, such as flash sales, exclusive rewards, or subscription models, to convert their affinity into higher transaction volumes. Most critically, Cluster 1 requires "Urgent Intervention" to mitigate the risk of churn among these 156 customers. This must involve deep-dive feedback loops to identify the root causes of their dissatisfaction, followed by the immediate deployment of compensatory incentives to re-establish system trust before they exit the ecosystem entirely.

4. CONCLUSION

The integration of behavioral and emotional metrics via a data-normalized K-Means pipeline successfully bridges the established literature gap, proving that customer satisfaction and purchasing frequency are distinct yet deeply intertwined pillars of e-commerce loyalty. By mapping 450 customer records into three robust, non-overlapping segments verified by a strong Silhouette Coefficient of 0.62, this study delivers on its initial objectives to provide a highly granular and representative customer typology. The empirical findings validate the necessity of data preprocessing, demonstrating that scaling preventing variables from biasing Euclidean distances, while revealing crucial strategic insights—such as the transactional "satisfaction gap" in Cluster 0 and the severe churn risks associated with low satisfaction in Cluster 1. Ultimately, this structural alignment transforms raw analytical data into a reliable foundation for personalized, targeted Customer Relationship Management (CRM) interventions that enhance promotional efficiency and corporate profitability.

Moving forward, the success of this unified framework opens compelling prospects for future methodological developments and real-world e-commerce applications. Future studies can build upon these results by expanding the data pipeline into dynamic, real-time clustering systems that integrate time-series behavioral changes and shifting sentiment data. Incorporating advanced machine learning architectures, such as hybrid evolutionary algorithms or deep clustering networks, could further refine segment boundaries as e-commerce datasets grow in complexity. From a practical application standpoint, businesses can leverage these isolated archetypes to build automated marketing engines that trigger predictive product personalization, dynamically adjust loyalty rewards, and deploy automated customer service recovery protocols to mitigate churn before it manifests transactionally.

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