

## CLUSTERING OF E-WALLET USAGE BASED ON TRANSACTION PATTERNS USING K-MEANS

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**Abstract**—The use of e-wallets has grown rapidly along with the increasing demand for fast and convenient digital financial transactions. This development requires service providers to better understand user behavior through transaction pattern analysis. This study aims to cluster e-wallet users based on their transaction patterns using the K-Means algorithm. The data analyzed include several key variables, namely transaction frequency, transaction value, transaction type, and transaction time. The K-Means method is applied to group users with similar transaction characteristics through data normalization and optimal cluster determination. The results indicate that e-wallet users can be divided into several distinct segments with significantly different transaction patterns. Each cluster represents specific user behavior characteristics, such as high-frequency users, high-value transactions, or time-based usage patterns. In conclusion, this study contributes to the growing body of research on digital payment analytics by demonstrating the applicability of the K-Means clustering algorithm for transaction-based user segmentation. The findings provide empirical evidence that behavioral transaction data can be systematically structured into meaningful user groups through unsupervised learning techniques. This research extends prior studies by integrating clustering evaluation methods to ensure optimal segmentation results, thereby offering a methodological reference for future studies in fintech data analysis.

**Keywords:** clustering; e-wallet; k-means; transaction pattern; user segmentation.

**Abstrak**—Penggunaan e-wallet berkembang pesat seiring meningkatnya kebutuhan akan transaksi keuangan digital yang cepat dan praktis. Perkembangan ini menuntut penyedia layanan

untuk memahami perilaku pengguna secara lebih mendalam melalui analisis pola transaksi. Penelitian ini bertujuan untuk mengelompokkan pengguna e-wallet berdasarkan pola transaksi menggunakan algoritma K-Means. Data penelitian mencakup beberapa variabel utama, yaitu frekuensi transaksi, nilai transaksi, jenis transaksi, dan waktu transaksi. Metode K-Means digunakan untuk membentuk kelompok pengguna dengan karakteristik transaksi yang serupa melalui proses normalisasi data dan penentuan jumlah cluster optimal. Hasil penelitian menunjukkan bahwa pengguna e-wallet dapat dikelompokkan ke dalam beberapa segmen yang memiliki perbedaan signifikan dalam pola transaksi. Setiap cluster merepresentasikan karakteristik perilaku pengguna yang berbeda, seperti pengguna dengan frekuensi tinggi, nilai transaksi besar, atau penggunaan pada waktu tertentu. Simpulan dari penelitian ini adalah bahwa metode K-Means efektif digunakan untuk mengidentifikasi segmentasi pengguna e-wallet, sehingga hasilnya dapat dimanfaatkan oleh penyedia layanan dalam menyusun strategi pemasaran, personalisasi layanan, dan peningkatan kualitas pengalaman pengguna.

**Kata Kunci:** clustering; e-wallet; k-means; pola transaksi; segmentasi pengguna.

### INTRODUCTION

The development of information and communication technology has driven significant transformation in the financial sector, particularly through the utilization of digital payment systems. One rapidly growing innovation is the electronic wallet (e-wallet), which enables users to conduct financial transactions conveniently, quickly, and securely through mobile devices (Paramitha & Wibowo, 2026). The advantages of e-wallets, such

as ease of access, time efficiency, and high security levels, have made them increasingly popular and widely used in various activities, including online shopping, bill payments, transportation services, and other digital-based services (Baiq Nikum Yulisasih, Herman, & Sunardi, 2024). In Indonesia, the growth of e-wallet usage continues to increase in line with the high penetration of digital technology and the public's need for efficient cashless payment systems (Akande, Asani, & Dautare, 2024).

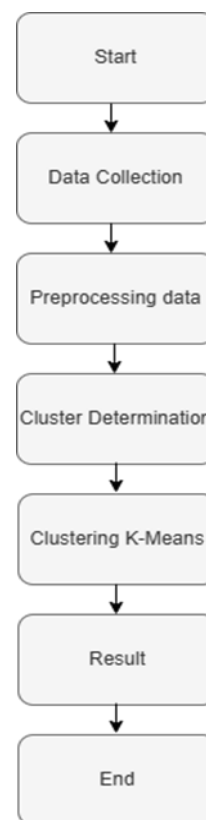
Despite the increasing adoption of e-wallets across various age groups and user backgrounds, understanding user behavior and transaction patterns remains relatively limited. Each user has different transaction characteristics influenced by factors such as frequency of use, transaction value, types of services utilized, and transaction timing (Saputra, Fadhilah, & Mangkuto, 2024). These differences indicate that e-wallet users are not homogeneous, thus requiring an analytical approach to systematically understand user behavior patterns (Irawan, Rahman, & Wibowo, 2025). Several previous studies have examined transactional data in digital payment systems and user segmentation using clustering techniques. For instance, clustering based on RFM and K-Means has been applied to top-up users of e-wallet services (Ranja, Ginting, Putra, & Bukit, 2026) and QRIS tap transactions in public transport (Paramitha & Wibowo, 2026). Other research has used financial transaction patterns to profile users with clustering methods (Pratama, 2024). Studies on cashless payment behavior in e-commerce have also employed cluster analysis (Sugiono & Nugraheni, 2023). However, quantitative studies that specifically cluster e-wallet users based on detailed transaction behavior patterns remain relatively limited.

One approach that can be used to identify user characteristics is clustering techniques, which aim to group data based on similarities in certain attributes (Khoiri, Kotjoprayudi & Eskaluspita, 2025). The K-Means algorithm is one of the most widely used clustering methods due to its simplicity, efficiency, and ability to handle large datasets (Nugroho, Rafhina, Ananda, & Gunawan, 2024). In the context of e-wallets, the application of K-Means enables the grouping of users based on similar transaction patterns (Siswanto & Rinofah, 2020), resulting in clearer and more measurable user segmentation (Rusnani, Enita, Tukidi, & Haryanto, 2021). This segmentation is essential for e-wallet service providers to support strategic decision-making, such as designing more personalized services, developing new features, and formulating targeted marketing strategies (Pratama & Arianto, 2023).

Based on the background and identified research gap, this study aims to cluster e-wallet users based on transaction patterns using the K-Means algorithm. The results are expected to contribute to a better understanding of e-wallet user behavior characteristics and serve as a foundation for developing service strategies and product innovations tailored to the needs of each user segment.

## MATERIALS AND METHODS

This study employs a quantitative approach using a simulated experimental method to analyze e-wallet user transaction patterns. This approach was selected because it enables objective numerical data processing and the implementation of an unsupervised machine learning algorithm, namely K-Means Clustering, to form user segmentation based on similarities in transaction characteristics (Worabai, E., Muhammad, A. H., & Hidayat, 2023). The main objective of this method is to generate user groups that represent transaction behavior patterns in a data-driven and replicable manner. To provide a clear overview of the research procedure, the overall methodological framework is illustrated in Figure 1.



Source: (Research Results, 2026)

Figure 1. Research Flow Diagram

### Data Description

The data used in this study consist of secondary data in the form of e-wallet user transaction records. Since real transaction data were not accessible due to privacy and confidentiality constraints, this study utilized simulated data generated based on common e-wallet transaction patterns reported in previous studies and statistical reports on digital payment usage (Tabianan, Velu, & Ravi, 2022). The attributes used include transaction frequency, average transaction value, dominant transaction category, duration of e-wallet usage, and the most frequent transaction time. These attributes were selected because they comprehensively represent user transaction behavior.

The research population includes e-wallet application users represented in the dataset. This study utilized 850 transaction records generated through a simulation process to ensure sufficient variation in user transaction behavior and to produce representative clustering results. The simulated dataset was developed using Python based on transaction characteristics reported in previous studies and statistical reports on digital payment usage. Data references were also obtained from publicly available repositories such as Kaggle and the UCI Machine Learning Repository to guide the simulation structure.

### Data Preprocessing

Before performing the clustering process, the data underwent preprocessing to ensure data quality and consistency. This stage included data cleaning from missing values, duplicates, and anomalous data; transformation of categorical data into numerical format; data normalization using Min-Max Scaling or Standard Scaling; and feature selection to retain the most relevant attributes for the clustering process. The Standard Scaling formula is expressed as (1):

$$X' = \frac{X - \mu}{\sigma} \quad (1)$$

### Determination of the Optimal Number of Clusters

The determination of the optimal number of clusters was conducted prior to applying the K-Means algorithm. The Elbow Method was used to analyze the within-cluster sum of squares (WCSS) to identify the elbow point indicating the optimal number of clusters, while the Silhouette Score was used to evaluate the separation quality between clusters (Nasution & Rakhmawati, 2023). The value of K was determined based on the evaluation results of these two methods to obtain optimal clustering results.

$$WCSS = \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \quad (2)$$

### K-Means Clustering Process

The clustering process was carried out using the K-Means algorithm by first determining the value of K and then initializing the centroids randomly. The distance between data points and centroids was calculated using Euclidean Distance. Each data point was then assigned to the nearest cluster (Patimah, Ermatita, & Chamidah, 2021). The centroid positions were updated based on the mean value of the data points within each cluster, and this process was repeated until convergence was achieved, meaning that the changes in centroid positions were no longer significant.

$$dx_i \mu_k = \sqrt{\sum_{j=1}^n z(x_{ij} - \mu_{kjz})^2} \quad (3)$$

### Evaluation and Visualization

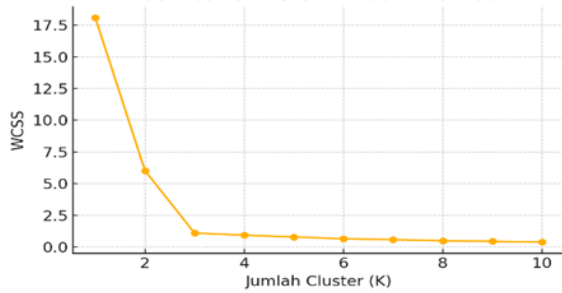
The evaluation of clustering results was performed using the Silhouette Coefficient to measure cluster cohesion and separation. In addition, clustering results were visualized in a two-dimensional scatter plot using dimensionality reduction techniques such as Principal Component Analysis (PCA) (Koswara, 2025). The characteristics of each cluster were then analyzed to interpret user segmentation, such as identifying active users, high-value transaction users, or users with seasonal transaction patterns (Ardiansyah, Aryanti, Fitriani, & Royadi, 2025).

### Implementation Tools

All data processing and analysis procedures were implemented using the Python programming language, supported by libraries such as pandas for data manipulation, scikit-learn for implementing the K-Means algorithm and clustering evaluation, and matplotlib for visualization. The implementation structure was systematically designed to ensure that the research process can be reproduced by other researchers.

## RESULTS AND DISCUSSION

The first step in performing clustering analysis is determining the optimal number of clusters. In this study, the Elbow Method was used to identify the appropriate number of clusters. This method was conducted by calculating inertia (the sum of squared distances between data points and cluster centroids) for various numbers of clusters, then selecting the number at which the decrease in inertia begins to slow down significantly. The results are presented in Figure 2.



Source: (Research Results, 2026)  
 Figure 2. Elbow Method Graph

Figure 2 illustrates the relationship between the number of clusters and the inertia value. A significant decrease in inertia was observed from the first cluster to the third cluster. The Within-Cluster Sum of Squares (WCSS) value at  $K = 3$  was 1,842.37, while further increases in  $K$  resulted in only marginal reductions. After the third cluster, the inertia curve became more gradual, indicating that adding more clusters did not significantly reduce data variance. Therefore, three clusters were selected as the optimal number. To further validate the clustering quality, the Silhouette Score was calculated. The average Silhouette Coefficient obtained for  $K = 3$  was 0.61, indicating good cluster cohesion and separation. A value above 0.5 suggests that the clustering structure is well defined and that data points are appropriately grouped within their respective clusters.

After determining the optimal number of clusters, the K-Means algorithm was applied to group e-wallet users based on three main variables influencing transaction patterns:

1. Transaction frequency per week
2. Average transaction amount per user
3. Number of transaction types used

Based on the clustering results, e-wallet users were divided into three distinct groups, each demonstrating different transaction characteristics. The clustering output is presented in Table 1.

Table 1. E-Wallet User Clustering Results

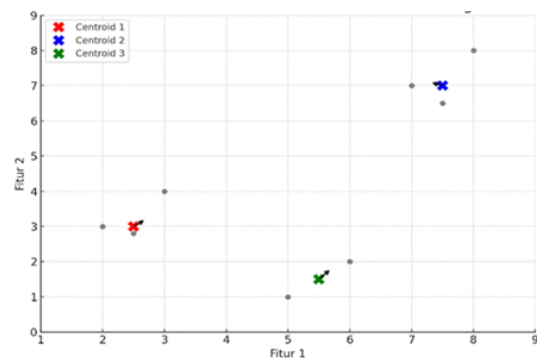
No	Weekly Transaction Frequency	Average Transaction Value (IDR)	Transaction Types	Cluster
1	3	10,000	1	0 (Passive)
2	10	500,000	5	2 (Active)
3	1	5,000	1	0 (Passive)
4	7	200,000	4	1 (Regular)
5	5	150,000	3	1 (Regular)
6	9	450,000	5	2 (Active)
7	2	8,000	1	0 (Passive)
8	11	600,000	6	2 (Active)
9	6	250,000	4	1 (Regular)
10	3	9,000	1	0 (Passive)

Source: (Research Results, 2026)

Table 1 shows the distribution of users into three clusters based on transaction behavior characteristics. Each cluster is formed according to differences in transaction frequency, transaction amount, and transaction type diversity.

Further analysis of the centroid values revealed clear distinctions among the three clusters. Cluster 0 (Passive Users) has an average transaction frequency of 2.25 transactions per week, with an average transaction value of Rp 8,000 and an average of 1.00 transaction type. This cluster represents users with minimal transaction activity, both in terms of frequency and monetary value. Cluster 1 (Regular Users) shows a moderate behavioral pattern, with an average transaction frequency of 6.00 transactions per week and an average transaction value of Rp 200,000. The average number of transaction types used in this cluster is 3.67, indicating more diverse usage compared to passive users. This segment reflects consistent and stable engagement with the e-wallet platform. Cluster 2 (Active Users) demonstrates the highest level of engagement, with an average transaction frequency of 10.00 transactions per week and an average transaction value of Rp 516,667. The average number of transaction types in this cluster is 5.33, suggesting a broader and more intensive use of available transaction features.

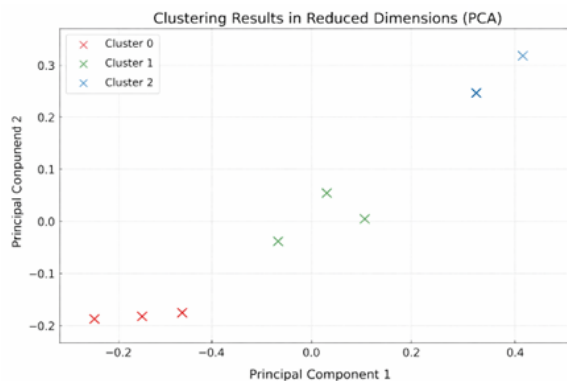
These centroid differences confirm a progressive behavioral segmentation pattern, where transaction intensity and diversity systematically increase from Cluster 0 to Cluster 2. The results indicate that user engagement levels can be clearly differentiated based on frequency, monetary contribution, and transaction variety, supporting the effectiveness of the K-Means clustering approach in identifying meaningful user segments. To provide a clearer interpretation of the clustering mechanism, Figure 3 illustrates how the K-Means algorithm assigns data points to the nearest centroid.



Source: (Research Results, 2026)

Figure 3. Illustration of the K-Means Clustering Process

In Figure 3, grey points represent individual observations, while the X markers indicate centroid positions. The visualization shows how data points are grouped based on proximity to the nearest centroid during iterative optimization.



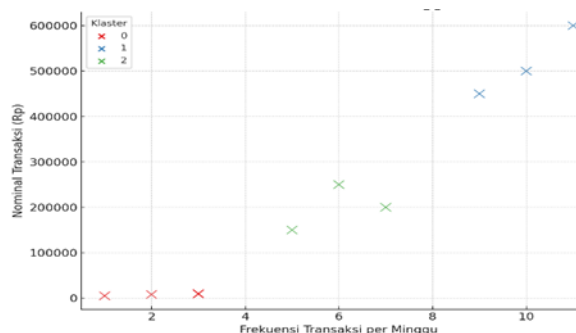
Source: (Research Results, 2026)

Figure 4. PCA Visualization of E-Wallet User Clusters

Figure 4 presents the clustering visualization after dimensionality reduction using Principal Component Analysis (PCA). The scatter plot illustrates the distribution of e-wallet users across two principal components, namely Principal Component 1 and Principal Component 2. Each point represents an individual observation, while different colors indicate the cluster membership generated by the K-Means algorithm. The visualization shows three clearly separated clusters, indicating that the clustering structure is well defined in the reduced dimensional space. The PCA projection confirms that the K-Means algorithm successfully groups users into distinct behavioral segments based on their transaction patterns. Clustering evaluation was conducted using several approaches. The Silhouette Coefficient was used to measure cohesion and separation between clusters. Scatter plot visualization using PCA was applied to observe cluster separation in reduced dimensions. In addition, cluster characteristic analysis was performed to examine behavioral profiles such as passive, regular, and active users.

As shown in Figure 5, the two-dimensional scatter plot illustrates the distribution of e-wallet users based on transaction frequency per week and average transaction value. The visualization clearly demonstrates three distinct behavioral segments. Cluster 0 represents low-engagement users with infrequent transactions and lower average transaction amounts. Similar findings have been reported in user segmentation research, where low-activity behavioral clusters are often linked to limited usage familiarity or lower adoption (Pratama, 2024) and are characterized by

transactional patterns that reflect minimal engagement compared with other segments.



Source: (Research Results, 2026)

Figure 5. Cluster Visualization Results

Cluster 1 denotes moderately active users, who exhibit consistent transaction frequencies and balanced monetary behavior. This segment is analogous to the “regular user” group identified in clustering studies of financial transactions, where such users form a stable base between occasional and highly active behaviors (Awaliyah, Budi Prasetyo, Muzayanah, & Lestari, 2024). Regular engagement in transaction activities suggests that this cluster may be responsive to incremental incentives aimed at increasing usage frequency, consistent with broader findings on how intermediate segments behave in digital finance environments.

Cluster 2 includes highly active users with high transaction frequency and significant monetary contribution. Research in similar contexts, such as e-commerce and QRIS/QR-based payment studies, has shown that clusters with higher engagement levels often represent users with greater dependence on digital payment services and higher digital financial literacy, which correlates with increased service utilization and transaction consistency (Ranja et al., 2026). These findings align with segmentation analyses in other domains, where high-value clusters contribute disproportionately to overall transaction volume and often require differentiated service strategies.

The identification of these clusters is consistent with previous clustering-based user segmentation studies that categorize users based on transactional behaviors and behavioral intensity (e.g., low, moderate, high engagement) (Pratama, 2024). For instance, research involving profiling based on financial transaction patterns confirmed that clustering techniques like K-Means can reveal meaningful groupings with distinct behavioral characteristics and implications for targeted strategies (Pratama, 2024). Such structural similarity across studies strengthens the external validity of this research and confirms

clustering's effectiveness in the domain of digital payment analytics.

Overall, the clustering results support data-driven design of differentiated strategies. Passive users show patterns that suggest further educational and engagement facilitation, consistent with behavioral segmentation literature that emphasizes tailored engagement for lower clusters (Awaliyah et al., 2024). Regular users can benefit from loyalty and personalized incentives to encourage higher engagement, while highly active users represent key contributors whose retention and feature adoption can be enhanced through premier service offerings and personalization, paralleling findings in customer analytics research across digital transaction ecosystems.

### CONCLUSION

This study confirms that the implementation of the K-Means clustering algorithm is effective in identifying e-wallet user segmentation based on transaction behavior patterns. The analysis successfully generated optimal clusters as determined by the Elbow method and Silhouette Score evaluation, indicating well-defined and compact group structures. The resulting clusters reveal significant differences in transaction frequency, average transaction value, usage duration, and dominant transaction categories, enabling the identification of distinct user segments such as active users, high-value users, and moderate or seasonal users. These findings demonstrate that data-driven clustering provides deeper behavioral insights compared to conventional descriptive analysis. Academically, this study contributes to the application of unsupervised learning methods in the digital payment domain, particularly in transaction-based behavioral analysis. Practically, the identified user segmentation can serve as a strategic foundation for e-wallet providers to design targeted marketing strategies, enhance feature development, and improve service personalization to strengthen user engagement and loyalty.

Despite the meaningful findings, this study has several limitations. First, the research utilized simulated transaction data due to limitations in accessing real user transaction records, which may not fully capture the complexity of real-world behavioral patterns. Second, the clustering process relied solely on the K-Means algorithm, which assumes spherical cluster structures and may not optimally capture more complex behavioral distributions. Third, the variables used in this study were limited to transaction frequency, average transaction value, and number of transaction types, without incorporating temporal

dynamics or contextual factors such as demographic characteristics or promotional influences.

Based on these limitations, future research may explore alternative clustering algorithms such as hierarchical clustering or DBSCAN to compare segmentation robustness. Further studies could also incorporate more complex temporal and contextual variables, as well as utilize large-scale real-time transaction data, to produce more dynamic, generalizable, and accurate segmentation models.

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