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Customer Segmentation of Mobile Banking Users Using Feature Engineering and K-Means Clustering

Hijja Ania[1], Mahyuddin[1], Elviawaty Muisa Zamzami[1]

[1]*Universitas Sumatera Utara, Indonesia*

**Corresponding Author: Hijja Ania*
Email: hijjaania@gmail.com

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Abstract

The increasing adoption of mobile banking has necessitated deeper insights into user behavior to enable banks to design personalized and targeted marketing strategies. This study aims to segment mobile banking customers based on their transaction patterns, specifically in the purchase of prepaid mobile credit and internet packages, using feature engineering techniques and the K-Means clustering algorithm. A dataset comprising over one million transactions from a regional bank in North Sumatra, Indonesia, was analyzed. Behavioral and time-based features were extracted to capture customer activity levels, transaction values, temporal preferences, and product usage. The Elbow Method identified five optimal clusters, each representing unique user profiles, including occasional users, regular low-value users, premium users, heavy users, and moderate-consistent users. Findings indicate strong operator loyalty and consistent transaction timing across segments, especially in early-month activity. The results offer practical implications for financial institutions seeking to enhance customer engagement, retention, and service personalization through behavior-based segmentation strategies. This study also contributes methodologically by showcasing the utility of unsupervised machine learning in deriving customer insights from transactional data without relying on sensitive demographic information.

Introduction

The rapid advancement of digital technology has fundamentally reshaped consumer behavior, particularly in the financial services sector (Muslim, 2024; Singh et al., 2024; Arcot et al., 2024). This transformation accelerated during the COVID-19 pandemic, which compelled consumers to adopt digital transaction methods for reasons of safety, convenience, and efficiency (Brownell, 2021; Arcot et al., 2024). Among these innovations, mobile banking has become a critical channel, enabling users to conduct financial transactions anytime and anywhere (Mamashli & Zolfani, 2022; Ibragimov & Najmiddinov, 2025).

In countries like Indonesia, where mobile penetration is high and digital service adoption is growing rapidly, mobile banking plays a pivotal role in meeting daily consumer needs especially for basic services such as purchasing mobile credit and internet data packages. These transactions not only occur frequently but also reflect evolving user behavior in an increasingly digital financial ecosystem (Putrevu & Mertzanis, 2024; Challoumis, 2024)

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Understanding user behavior is crucial for financial institutions aiming to deliver personalized services and retain customer loyalty (Cardoso & Cardoso, 2024; Nurhilalia & Saleh, 2024). Customer segmentation is a key marketing strategy that categorizes users into distinct groups based on similar characteristics or behaviors. In mobile banking, such segmentation helps reveal patterns in transactions and preferences that inform targeted promotions and service innovation (Tabianan et al., 2022; Pratama & Putri, 2024; Prasetyaningrum et al., 2025). However, traditional segmentation methods often based solely on demographics or general usage fail to capture the complexity of modern digital consumer behavior. This limitation calls for a shift towards behavior-based segmentation models that leverage user activity data, particularly transactional histories (Paramasivan, 2024; Liu & Hu, 2025; Kasemrat & Kraiwanit, 2025)

Behavioral segmentation allows banks to go beyond surface level categorizations to understand users' intents, preferences, and financial habits (Barone et al., 2024; Munira, 2025; Abdallah et al., 2025). Yet, the raw transactional data is typically unstructured and voluminous, posing challenges for direct analysis. To address this, feature engineering is employed to transform raw data into meaningful variables that better reflect customer behavior. Feature engineering enhances the interpretability of data by creating new features or refining existing ones such as transaction frequency, average spending, time-of-day usage, and preferred service types. This transformation is critical for preparing data for advanced analytical techniques, including clustering.

K-Means clustering, a widely used unsupervised machine learning algorithm, offers an efficient method for grouping users based on behavioral similarity without relying on predefined labels. Its simplicity and scalability make it well-suited for large-scale customer data analysis. By applying K-Means, banks can uncover natural clusters within their user base and design services tailored to the specific needs of each segment (Arunachalam & Kumar, 2018; Chitra & Heikal, 2024; Yang, 2024). Despite its advantages, the application of K-Means in mobile banking specifically for segmenting users based on mobile top-up and data package transactions remains underexplored. Most existing studies focus on general mobile banking adoption, satisfaction, or technology acceptance, with little attention to micro-level transactional behavior.

While clustering techniques like K-Means have been successfully used in sectors such as retail (Anita & Patil, 2022; Şentürk et al., 2024; Putri et al., 2024), healthcare (Matias et al., 2021), and banking (Benbrahim, 2021), their adoption in financial services especially in emerging markets is still limited. Factors such as technological readiness and data privacy concerns contribute to this gap. Moreover, few empirical studies focus specifically on behavior-driven segmentation based on recurring mobile banking transactions like top-ups and data purchases, even though these activities offer rich insights into user behavior.

This study addresses that gap by implementing a behavior-driven segmentation framework using feature engineering and the K-Means clustering algorithm. By analyzing anonymized mobile banking transactions from a regional bank in North Sumatra, Indonesia, this study aims to identify meaningful customer segments and generate actionable insights for improving service personalization and marketing effectiveness (Abidin & Octira, 2024; Kumalasari & Syahyunan, 2024).

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Methods

Research Design

This study adopts a quantitative, data-driven research approach involving the application of unsupervised machine learning for customer segmentation. The methodological workflow includes: (1) business understanding, (2) data collection, (3) data preprocessing, (4) feature engineering, (5) clustering using K-Means, and (6) evaluation and visualization. The primary aim is to uncover behavioral patterns among mobile banking users by analyzing their transactions for prepaid mobile credit and data package purchases.

Data Collection

The dataset used in this study was obtained from a regional bank in North Sumatra, Indonesia, comprising mobile banking transaction records from January to December 2023. These transactions relate specifically to the purchase of mobile airtime and internet data packages. The dataset includes six key attributes:

Table 1. Atribut Raw Data Mobile Banking

No.	Nama Atribut	Tipe Data
1	chanel_type	symbolic
2	trx_value	numeric
3	received_time	datetime
4	product_name	symbolic
5	operator_code	symbolic
6	id_pelanggan	combination

Explanation of attributes contained in the raw dataset, namely: 1) channel_type, customer attribute that indicates the type of channel used to make transactions. Symbolic data type in the form of text that represents different category values but has no numeric or sequential meaning. This feature is used to analyze the pattern of use of various types of communication channels by customers; 2) Trx_value, this attribute shows the transaction value in currency units. Numeric data type in the form of numbers. This feature is used to measure the amount of transactions made by customers; 3)Received_time, this attribute shows the specific time when the transaction was made and received by the system. The datetime data type represents information about the date and time. This feature is used to track the time of transactions made by customers; 4) Product_name, this attribute shows the name of the product purchased in the transaction. Symbolic data type in the form of text that represents different categories but has no numeric or sequential meaning. This feature is used to identify specific products involved in each transaction; 5) Operator_code, this attribute shows the telecommunications operator code that provides services for the transaction. Symbolic data type in the form of text that represents different categories but has no numeric or sequential meaning. This feature is used to identify the telecommunications operator involved in the transaction; 6) Id_pelanggan, this attribute shows the unique identification of the customer who made the transaction. The combination data type is a combination of two values combined. This attribute is used to track individual customer transactions

Identifying Data Quality

After understanding the data structure and managing various customer attributes, the next step is to identify the quality of the data that enters the Exploratory Data Analysis (EDA) stage, with the aim of ensuring that the dataset reflects good bank data. According to research (E. A. Dawood et al., 2019), good bank data must have the following characteristics: 1)

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Completeness: Data must be complete with few or no missing values. Missing values can cause bias in analysis and predictive models, so they need to be identified and handled; 2) Cleanliness: Data must be free from unreasonable and inconsistent outliers. Outliers can interfere with analysis and prediction results, so they need to be identified and handled properly; 3) Consistency: Data must be consistent in format and representation. Inconsistencies in data can be in the form of errors in data entry, inconsistent formats, or data duplication.

A brief overview of the data used in this study is shown in Table 3.2 which shows that there are still missing values with a value of 1751.

Tabel 1. Overview data penelitian

Description	Value
Number of Rows	1.048.575
Number of Columns	6
Missing Values	1751
Categorical Data Type	66.67%
Numeric Data Type	33.33%
String Data Type	66.64%

Source: Bank Daerah Sumatera Utara

Several preprocessing steps were conducted to clean and prepare the data for clustering: 1) Date and time formatting: The received_time field was converted into a datetime object; 2) Missing value handling: Null entries were either imputed or removed based on their relevance; 3) Standardization: Numerical features were scaled using z-score normalization to ensure equal weight in the clustering process; 4) Categorical encoding: Symbolic variables were transformed into numerical formats where necessary.

Feature Engineering

Feature engineering was a crucial step to extract meaningful indicators from raw transaction data. Two main types of features were constructed: transaction-based and time-based.

Tabel 3. Feature Engineering pada data transaksi

Category	Component	Feature	Description
Transaction Based	Frequency	total_transactions	Total number of customer transactions
		transactions_per_month	Median number of transactions per month
	Value	avg_trx_value_per_month	Average transaction value per month
		max_trx_value_per_month	Maximum transaction value in a month
	Product Diversity	unique_products	Number of different operators used
		most_frequent_product	Most frequently used operator
Time Based	Consistency	std_days_between_trx	Standard deviation of the number of days between transactions

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Category	Component	Feature	Description
	Seasonality	seasonal_preference	Preference for transaction time in months; Early month: 1st-10th Mid month: 11th-20th Late month: 21st-last
		time_of_day_preference	Preference for transaction time in days; Morning: 06.00 - 11.59 Afternoon : 12.00 - 17.59 Evening: 18.00 - 21.59 Night : 22.00 - 05.59

These engineered features capture both the frequency, magnitude, and temporal regularity of user behavior, which are vital for behavioral segmentation.

Clustering with K-Means Algorithm

The K-Means clustering algorithm was used due to its scalability and effectiveness in segmenting large datasets (Jain, 2010). The algorithm partitions the dataset into *k* clusters, minimizing the within-cluster sum of squares (WCSS) through iterative centroid optimization. Euclidean distance was used as the similarity metric.

Determining Optimal Number of Clusters

The Elbow Method was employed to determine the optimal number of clusters. This involves plotting the WCSS for different values of *k* (from 1 to 20) and identifying the "elbow" point where the rate of decrease sharply declines. In this study, the optimal number of clusters was determined to be k = 5, as the curve began to flatten at that point.

Cluster Evaluation and Visualization

To interpret the clustering results, Principal Component Analysis (PCA) was applied for dimensionality reduction and visualization. This enabled a 2D projection of the multi-dimensional cluster space. Each cluster's centroid and distribution were analyzed by comparing mean values across all engineered features.

Results and Discussion

Optimal Number of Clusters

Using the Elbow Method, the within-cluster sum of squared errors (WCSS) was calculated for values of *k* ranging from 1 to 20. As shown in the plot below (Figure 1), the WCSS value rapidly decreased up to $k = 5$, after which the rate of decrease plateaued. This "elbow" point indicates that five clusters strike a good balance between compactness and simplicity.

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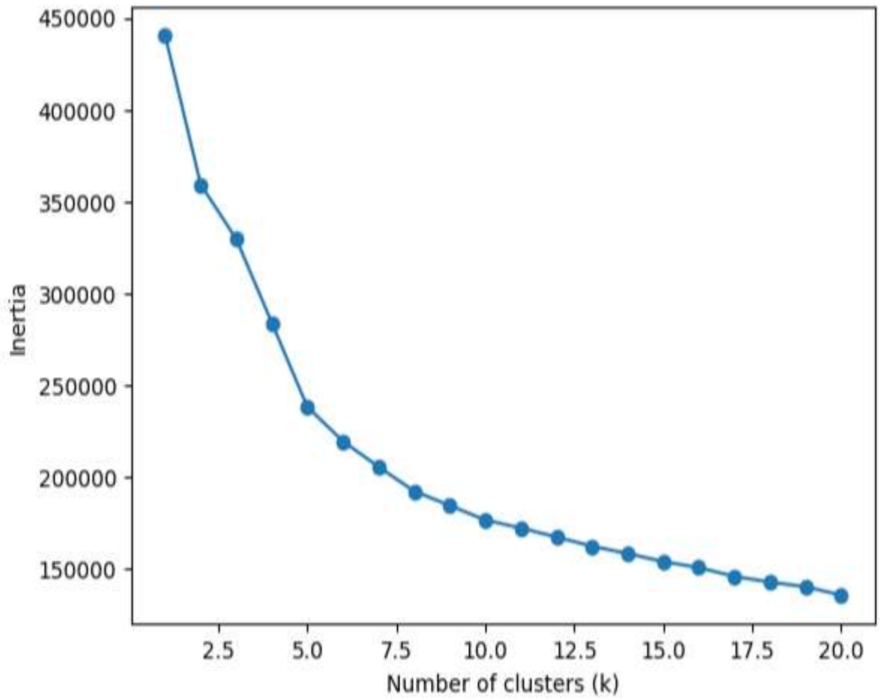

Figure 1. Elbow Curve for Cluster Selection

Cluster Visualization

To better understand the clustering structure, the high-dimensional feature space was reduced to two dimensions using Principal Component Analysis (PCA). The 2D scatter plot (Figure 2) illustrates a reasonably well-separated clustering result, with minimal overlap across groups, indicating that the engineered features effectively captured unique customer behavior patterns.

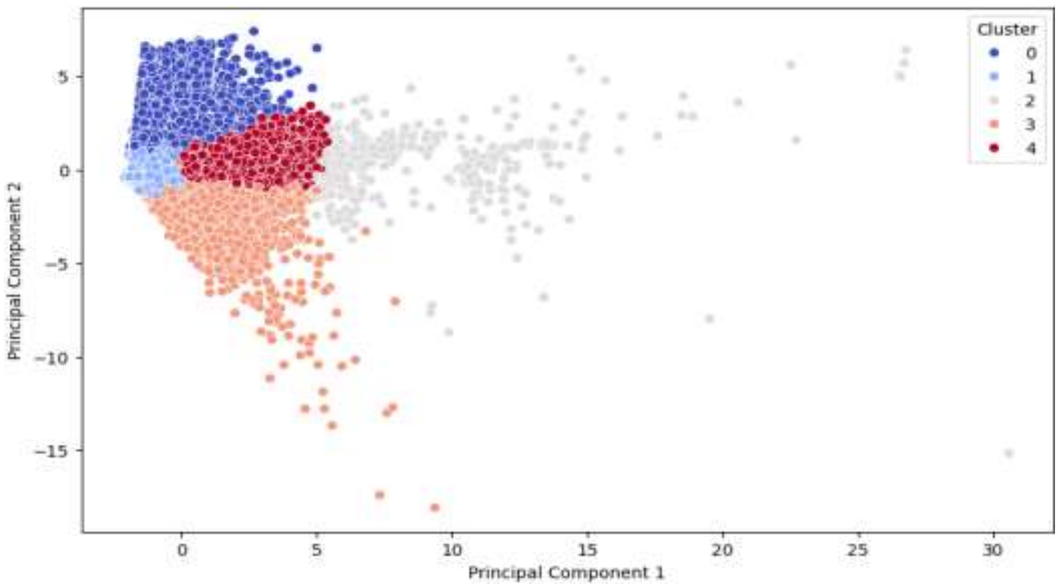

Figure 2. Visualization of Clusters using PCA

Cluster Profile Summary

The K-Means algorithm produced five distinct customer segments, each with unique transactional and temporal characteristics. Table 1 summarizes the average feature values for each cluster.

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Table 4. Cluster Characteristics

Cluster Group	0	1	2	3	4
total_transactions	5	6	24	39	9
avg_trx_value_per_month	54554	32827	212177	56819	89506
max_trx_value_per_month	84086	50033	612121	116282	122916
std_days_between_trx	86	13	20	13	18
most_frequent_product	Telkomsel	Telkomsel	Telkomsel	Telkomsel	Telkomsel
time_of_day_preference	Afternoon	Afternoon	Morning	Morning	Morning
seasonal_preference	Early month	Early month	Early month	Early month	Early month

Cluster Interpretations

Cluster 0: Occasional Users

Characterized by low transaction frequency and moderate transaction values, with high irregularity (std. deviation of 86 days). These users prefer afternoon transactions at the beginning of the month.

Cluster 1: Regular Low-Value Users

This group transacts more frequently than Cluster 0 but spends significantly less. Despite low value, their behavior is relatively consistent.

Cluster 2: Premium Customers

High-value, high-frequency users with a large maximum transaction value. This group represents the most lucrative segment and prefers morning transactions.

Cluster 3: Heavy Users

These users have the highest transaction frequency but only moderate spending. They show highly regular behavior, suggesting strong engagement.

Cluster 4: Moderate and Consistent Users

This group is balanced in both transaction frequency and value. They represent a stable customer base with high potential for loyalty development.

All clusters shared a strong preference for the Telkomsel operator, indicating brand dominance. Transaction timing showed behavioral patterns: afternoon preference for low spenders (Clusters 0 and 1), and morning preference for high and moderate spenders (Clusters 2–4). There is a consistent seasonality pattern, with all groups preferring transactions in the early part of the month, possibly linked to salary disbursements or billing cycles.

Behavioral Insights and Managerial Implications

The findings of this study provide valuable insights into customer behavior in mobile banking environments, particularly for prepaid mobile credit and data package transactions. The clustering results revealed five distinct user segments, each demonstrating different levels of engagement, transactional value, and behavioral regularity. These segments offer a robust foundation for banks to implement targeted marketing strategies and personalized service delivery.

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For instance, Cluster 2 (Premium Customers), with the highest transaction values, represents a highly profitable segment. Banks could develop exclusive loyalty programs, early access promotions, or premium support services tailored to their needs. Conversely, Clusters 0 and 1 (Occasional and Low-Value Users) might benefit from incentivization strategies aimed at increasing engagement, such as cashback offers, discounts on transaction fees, or gamified reward schemes.

The Heavy Users in Cluster 3, while not spending as much per transaction, show a high frequency of interaction with the mobile platform. This segment could be engaged through subscription packages or bundle deals that reward volume rather than transaction size. Meanwhile, Cluster 4 represents a stable user group that may be nurtured into higher-value clients through upselling or cross-selling based on their consistent behavior.

Understanding the temporal preferences of each segment such as time of day or time of month enables micro-targeted campaigns. For example, promotional messages sent in the morning might be more effective for Clusters 2 to 4, while Clusters 0 and 1 might respond better to afternoon offers.

Methodological Contributions

This study contributes methodologically by demonstrating how feature engineering combined with K-Means clustering can extract meaningful customer segments from raw transaction data. Unlike traditional segmentation approaches that rely solely on demographic or psychographic information, this study emphasizes the use of behavioral data to identify latent patterns in user activity.

Furthermore, the inclusion of both transaction-based features (e.g., volume and value) and time-based features (e.g., day-of-month and time-of-day preferences) allowed for a multidimensional analysis of user behavior. This approach aligns with prior research emphasizing the role of temporal dynamics in understanding digital consumer behavior (Zhao et al., 2021; Silva et al., 2021). The Elbow Method and PCA visualization served not only as diagnostic tools but also as communicative aids for interpreting the segmentation output, helping bridge technical analysis and managerial application.

Theoretical and Practical Implications

Theoretically, this study supports the notion that unsupervised learning techniques, such as K-Means, are powerful tools for market segmentation in the digital banking era. This aligns with prior findings in marketing analytics, where machine learning is increasingly replacing rule based segmentation methods (Dekimpe, 2020). From a practical standpoint, the results empower banks especially regional or mid-tier institutions to implement data-driven customer segmentation without requiring sensitive demographic information, thus maintaining compliance with data privacy regulations. This is particularly relevant in developing markets where banks may lack access to comprehensive user profiles but still possess extensive transactional data.

Limitations and Future Research

This study has several limitations. Fir st, the dataset was limited to transactions related to mobile top-ups and data package purchases, potentially excluding insights from broader financial behavior. Second, demographic variables such as age, gender, and income were not included due to data privacy constraints. Incorporating such data in future studies could enhance the interpretability and actionability of clusters.

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Future research may also explore the use of advanced clustering methods, such as DBSCAN, Gaussian Mixture Models, or deep learning-based autoencoders, to validate or refine the segments. Additionally, integrating real-time segmentation systems could allow banks to dynamically adapt their marketing strategies based on recent customer behavior.

Conclusion

This study has demonstrated the effectiveness of combining feature engineering with K-Means clustering to segment mobile banking users based on their transactional behavior. By analyzing a dataset of prepaid mobile and data package transactions, five distinct customer segments were identified, each with unique spending patterns, frequency, and temporal preferences. The segmentation outcomes provide valuable insights for banks aiming to enhance customer engagement through personalized strategies. High-value and high-frequency users (Clusters 2 and 3) can be prioritized for premium services and loyalty rewards, while lower-engagement segments (Clusters 0 and 1) may benefit from targeted promotions to boost retention. Moreover, time-based features such as preferred hours and dates of transaction provide additional layers for micro-targeted marketing.

Methodologically, this research contributes to the growing field of data driven marketing in financial services, showcasing how unsupervised machine learning can extract actionable insights from behavioral data, even in the absence of demographic information. The approach is particularly suited for regional banks or institutions with privacy restrictions that limit access to user identities. Future research could expand the scope of analysis by integrating additional datasets (e.g., transfers, bill payments), applying ensemble or hybrid clustering methods, and incorporating real-time analytics to support dynamic segmentation. Overall, this study underscores the strategic importance of behavioral analytics in shaping the next generation of mobile banking services.

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