Jurnal Asiimetrik: Jurnal Ilmiah Rekayasa Dan Inovasi
Accredited "**SINTA 3**" based on the Decree of Dirjendiktiristek, Number: 225/E/KPT/2022
Volume 7 Number 2, July 2025, Page 123-132
Website : http://journal.univpancasila.ac.id/index.php/asiimetrik/

p-ISSN 2655-1861
e-ISSN 2716-2923

Study of Awareness Patterns of Credit Card Users towards Ads with K-Means Clustering Algorithm

Studi Pola Kesadaran Pengguna Kartu Kredit terhadap Iklan dengan Algoritma K-Means Klastering

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Article information:

Received:
25/03/2025
Revised:
03/06/2025
Accepted:
20/06/2025

Abstract

In the era of digital transformation, credit cards have become an essential component of modern financial life, where users' understanding of card features significantly influences their financial decisions. Despite the wide use of advertising in the financial sector, limited studies have explored how credit card users in emerging markets respond to such campaigns. Addressing this gap, this study analyzes advertisement awareness patterns among credit card users in Indonesia using the K-Means Clustering algorithm on a dataset collected from August 2023 to March 2024. The study aims to examine levels of advertisement awareness, segment users based on their responses, and assess the implications of these segments for marketing strategies. The methodology follows the Knowledge Discovery in Database (KDD) process: data selection, preprocessing, transformation, clustering with K-Means, and evaluation using the Silhouette Score. Results reveal three distinct user clusters: (1) highly aware users in large cities with high exposure; (2) moderately aware users from mid-tier cities; and (3) low-awareness users despite high exposure, often from older age groups and lower SES backgrounds. The clustering yielded Silhouette Scores above 0.60, validating segmentation quality. The novelty lies in applying machine learning to segment awareness levels using a multi-city real-world dataset. The findings offer practical value for credit card providers to enhance targeted campaigns, improve user engagement, and allocate marketing resources more effectively across demographic segments.

Keywords: advertising, credit card users, clustering, K-Means.

***SDGs*:**

8 DECENT WORK AND ECONOMIC GROWTH

Abstrak

Di era transformasi digital, kartu kredit telah menjadi komponen penting dalam kehidupan finansial modern, di mana pemahaman pengguna terhadap fitur kartu sangat memengaruhi keputusan keuangan mereka. Meskipun iklan digunakan secara luas di sektor keuangan, masih sedikit studi yang mengeksplorasi bagaimana pengguna kartu kredit di pasar negara berkembang merespons kampanye tersebut. Untuk mengisi kekosongan ini, penelitian ini menganalisis pola kesadaran terhadap iklan di kalangan pengguna kartu kredit di Indonesia dengan menerapkan algoritma K-Means Clustering pada dataset yang dikumpulkan antara Agustus 2023 hingga Maret 2024. Penelitian ini bertujuan untuk mengkaji tingkat kesadaran iklan, mengelompokkan pengguna berdasarkan respons mereka, serta mengevaluasi implikasi segmentasi terhadap strategi pemasaran. Metodologi yang digunakan mengikuti tahapan *Knowledge Discovery in Database (KDD)*: seleksi data, pra-pemrosesan, transformasi, klasterisasi menggunakan K-Means, dan evaluasi menggunakan *Silhouette Score*. Hasil penelitian menunjukkan tiga klaster pengguna: (1) pengguna dengan kesadaran tinggi di kota besar dan frekuensi paparan tinggi; (2) pengguna dengan kesadaran sedang dari kota menengah; dan (3) pengguna dengan kesadaran rendah meskipun paparan tinggi, umumnya dari kelompok usia lanjut dan SES rendah. *Silhouette Score* di atas 0,60 menunjukkan segmentasi yang valid. Kebaruan penelitian ini terletak pada penerapan machine learning untuk segmentasi kesadaran iklan dengan dataset nyata dari berbagai kota di Indonesia. Temuan ini memberikan nilai praktis bagi penyedia kartu kredit untuk meningkatkan efektivitas kampanye, keterlibatan pengguna, dan alokasi anggaran pemasaran yang lebih tepat sasaran

Kata Kunci: iklan, kartu kredit, segmentasi, klastering, K-Means.

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1. INTRODUCTION

The use of credit cards has become an essential element of modern financial life, offering the convenience of electronic payments as well as benefits such as discounts, rewards, and purchase protection (Biradar, 2024; Fulford and Schuh, 2024). In this context, users' awareness of credit card features plays a key role in influencing their financial decisions, choice of card type, and level of usage and loyalty to the product. The rapid growth of the credit card industry is not only driven by an increase in the number of users but also by changes in consumer behavior and advances in financial technology (Rishi, Mallick and Shiva, 2024).

Data from Bank Indonesia shows that in August 2023, the number of credit cards in circulation in Indonesia reached 17.82 million units, up 0.73% from the previous month and an increase of 4.45% compared to the same period in the previous year (Rizaty, 2023). Although the number of credit cards in circulation increased, credit card transactions decreased by 4.85% in the same month (Laras, 2024).

In an increasingly competitive situation, it is important for financial companies to understand the advertisement awareness patterns of credit card users to develop more effective marketing strategies (Grodzicki, 2023). This understanding will help in identifying the right market segmentation, optimizing promotions, and devising marketing strategies that match customer preferences and needs (Ming, Chen and Li, 2021). Therefore, research on advertisement awareness patterns of credit card users is highly relevant to strengthening market penetration and customer relationships.

Segmenting credit card users based on ad awareness is crucial to ensure that marketing campaigns reach the right target audience (Medina, 2021). Users' level of awareness of the features, promotions, or benefits offered through advertisements greatly influences their decision to use a credit card (Qiu and Wang, 2024). With a deeper understanding of this awareness, credit card providers can develop more personalized, relevant, and focused marketing strategies, thereby increasing the effectiveness of advertising campaigns and user loyalty (Behera and Dadra, 2024). Segmentation also helps in more efficient allocation of advertising budget, thereby increasing the return on investment (ROI) of the marketing campaign (Soetan and Mogaji, 2024).

The K-Means Clustering Algorithm is one of the effective methods for segmenting credit card user data analysis (Hesananda and Agustian, 2024). K-means can be used to group users based on their awareness patterns of advertisements by dividing the data into clusters or segments (Sekaran, 2024). This technique allows companies to identify groups of users with similar characteristics, such as high, medium, or low awareness of ads (Hesananda, 2021).

With the application of K-Means Clustering, credit card companies can gain better insights into various market segments, making it easier for them to develop more targeted marketing strategies (Omol *et al.*, 2024). For example, users with high ad awareness may respond better to digital advertising campaigns, while segments with low awareness may require other approaches, such as educational programs and direct promotions (Tressa *et al.*, 2024). Another advantage of this method is its ability to provide fast and quantifiable results, such as the evaluation of cluster quality with the Silhouette Score, which allows validation of segmentation results for more accurate decision-making (Mozumder *et al.*, 2024).

Given these considerations, this study aims to identify patterns of advertisement awareness among credit card users in Indonesia by applying the K-Means clustering algorithm. The research specifically seeks to (1) analyze the level of users' awareness toward credit card advertisements; (2) segment users into distinct clusters based on their awareness levels, exposure frequency, and demographic characteristics; and (3) provide interpretations of each segment to inform strategic marketing decisions tailored to the needs and behaviors of different user groups.

The main contribution of this research lies in offering a data-driven segmentation model that integrates behavioral and demographic factors to inform credit card advertising strategies. From a methodological perspective, this study demonstrates the applicability of the KDD process combined with K-means clustering to uncover latent patterns in user awareness. Practically, the findings provide actionable insights for financial service providers to personalize their marketing efforts, enhance user engagement, and allocate advertising resources more efficiently across market segments.

2. METHODOLOGY

The research process implemented in this study adopts the Knowledge Discovery in Database (KDD) framework shown in Figure 1, which is well-recognized for transforming raw data into useful knowledge through a systematic and structured approach. The diagram above illustrates the sequential stages employed, starting from data selection to the interpretation of findings. Each stage plays a crucial role in ensuring the reliability and relevance of the final clustering results.

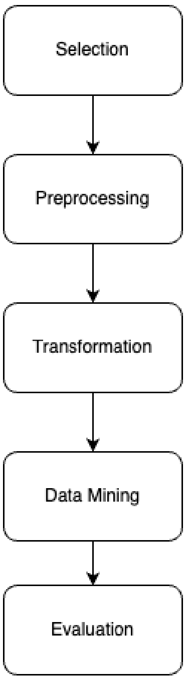


Figure 1. Research stages.

In the context of this study, the KDD process is particularly relevant due to the multidimensional nature of the dataset, which contains demographic, behavioral, and awareness-related variables. By following this framework, the analysis not only ensures methodological rigor but also supports the production of actionable insights that can inform real-world marketing strategies.

The stages are executed as follows: data selection aims to extract a subset of data that is both relevant and representative; preprocessing ensures data consistency and quality through cleaning and integration techniques; transformation converts categorical values into a format suitable for numerical analysis; data mining involves the application of the K-Means algorithm to identify meaningful clusters; evaluation assesses the validity of the clusters formed using the Silhouette Score; and finally, interpretation draws actionable conclusions from the results, outlining the implications for stakeholders in the financial and marketing sectors.

2.1. Selection

The dataset consists of 3,500 entries of credit card users collected from August 2023 to March 2024 across seven major Indonesian cities: Jakarta, Surabaya, Bandung, Semarang, Makassar, Medan, and Banjarmasin. The data includes demographic attributes (gender, age, education level), financial indicators (income, expenditure, utility percentage), brand of credit card used, frequency of advertisement exposure (scale 1-10), and self-reported level of advertisement awareness (scale 0–10). Initial data selection was performed to ensure completeness, consistency, and relevance to the research objective.

2.2. Preprocessing

This stage involved data cleaning, integration, and normalization. Missing values were handled using mean/median imputation, while redundant entries were removed to eliminate noise. Irrelevant fields such as system-generated IDs were excluded, focusing only on variables essential for clustering analysis. The cleaned dataset was then transformed to a standardized format suitable for computational modeling.

2.3. Transformation

Categorical attributes were converted into numerical values using label encoding. For example:

1. Gender: ‘L’ (Male) and ‘P’ (Female) were transformed into 1 and 2 respectively.
2. Education Level: Coded from 1 (elementary) to 6 (master’s degree).
3. Region and Brand: Each category was mapped to unique numerical values.

Socioeconomic classification (SES) was introduced by categorizing users based on their income and expenditure levels into SES A, B, C, and SES D/E. Additionally, utility percentages were grouped into low, medium, and high to reflect credit card usage intensity.

2.4. Data Mining

The K-Means algorithm is applied to group users into segments based on their awareness patterns of credit card advertisements. The K-Means algorithm was implemented using Python via Google Colab. Three primary attributes—ads awareness, ads frequency, and brand—were used as the basis for clustering, complemented by supporting attributes such as region, gender, age, education level, SES, and utility. The Elbow Method was used to determine the optimal number of clusters by analyzing the point where the Sum of Squared Errors (SSE) began to plateau.

2.5. Evaluation

The clustering results are evaluated using metrics such as silhouette score to assess the quality and interpretation of the clusters, followed by analysis and visualization of the characteristics of each user segment. This score measures the degree of cohesion within clusters and separation between clusters, with values ranging from -1 (poor clustering) to +1 (excellent clustering). A Silhouette Score above 0.60 is considered indicative of good cluster validity. The results were then visualized using scatter plots and cluster maps to facilitate interpretation.

2.6. Interpretation and Implication

Findings from the analysis were evaluated to identify implications for the marketing strategy, which was formulated based on the understanding gained from the analysis results.

3. RESULTS AND DISCUSSION

3.1. Selection

The dataset in this study was selected to ensure its relevance and quality in analyzing the advertisement awareness patterns of credit card users, using 3,500 data points from seven major cities in Indonesia: Jakarta, Banjarmasin, Semarang, Surabaya, Bandung, Makassar, and Medan. The variables considered include user demographics such as gender, age, education, income, expenditure, credit card brand, frequency of exposure to advertisements (scale 1-10), and level of awareness of advertisements (scale 0-10).

Table 1. Sample of dataset.

no	id	...	ads_freq	ads_awrns
1	08*******02	...	8	8
2	08*******24	...	5	8
3	08*******88	...	2	5
4	08*******20	...	null	1
5	08*******31	...	5	1
6	08*******04	...	7	7
7	08*******79	...	7	
8	08*******11	...	6	0
9	null	...	3	7
10	08*******73	...	null	3
11	08*******46	...	9	2
12	08*******98	...	4	5
13	08*******60	...	null	null
14	08*******97	...	5	8
15	08*******82	...	6	4

Data selection criteria included relevance, quality, completeness, and representation, followed by a preprocessing stage to clean the data from noise, integrate multiple sources, transform to a standardized format, and reduce dimensions. At this stage, relevant fields such as 'region', 'age', 'education', 'income,' 'outcome', 'utility_%', 'brand', 'ads_frequency', and 'ads_awareness' were selected, while irrelevant fields such as 'no' and 'id' were removed, thus ensuring that the data used provides important information regarding the demographics and behavior of credit card users. A sample of the dataset is shown in Table 1.

3.2. Preprocessing

This process includes the integration of data from multiple sources into one structured dataset, transformation to a more standardized format, and dimensionality reduction to improve computational efficiency. These steps support data mining analysis by ensuring that the data used is optimized for techniques such as clustering, prediction, or pattern generation. In data cleaning, it is important to ensure that the data is free of errors and invalid values; therefore, handling of missing values is done with approaches such as imputation of means or medians on important columns to fill in missing values. An example of such data cleaning can be seen in Table 2.

Table 2. Dataset samples after cleaning.

no	id	...	ads_freq	ads_awrns
1	08*******02	...	8	8
2	08*******24	...	5	8
3	08*******88	...	2	5
4	08*******20	...	2	1
5	08*******31	...	5	1
6	08*******04	...	7	7
7	08*******79	...	7	3
8	08*******11	...	6	0
9	08*******51	...	3	7
10	08*******73	...	5	3

3.3. Transformation

At this stage, data transformation is carried out to convert categorical values into numerical values so that they can be processed further in the next analysis. This transformation is performed on the \`gender\`, \`education_level\`, \`brand\`, and \`region\` columns. The following are the transformation steps that have been carried out:

1). Transformation of the 'gender' column: Initially the 'gender' column containing 'L' (Male) and 'P' (Female) values was transformed into numeric values. Initially the 'gender' column contains 'L' (Male) and 'P' (Female) values converted to numeric values. The 'L' value is changed to 1 and the 'P' value is changed to 2 (two), as can be seen in Table 3.

Table 3. Transformation of "Gender" column.

Gender	Into	Gender
L		1
P		2

2). The transformation of the 'education_level' column can be seen in Table 4. The education_level column has been transformed from categorical to numerical values to facilitate analysis. The education levels of 'elementary', 'secondary', 'high school', 'diploma', 'bachelor', and 'master's degree' are now represented with numbers 1 to 6 respectively. This transformation aims to simplify the data, enable the use of algorithms that require numerical input, and improve efficiency in the subsequent data analysis process.

Table 4. Transformation of column 'education_level'.

Education Level	Into	Education Level
SD		1
SLTP		2
SLTA		3
Diploma		4
Sarjana		5
S2/S3		6

3). The transformation of the 'brand' column can be seen in Table 5. The brand column, which originally contained the names of credit card brands, has been converted into numerical values to facilitate analysis. Nine credit card brands, including BCA, Mega, BRI, Mandiri, BNI, OCBC, Citibank, Permata, and HSBC, are now represented with numbers 1 to 9, respectively. This change from categorical to numerical values aims to improve efficiency in the subsequent data analysis process.

4). The \`region\` column has been transformed from city names to numerical values to facilitate data analysis. Six cities—Jakarta, Surabaya, Banjarmasin, Semarang, Bandung, and Medan—are now represented with numbers 1 to 6, respectively. This conversion from categorical to numerical data aims to improve efficiency in the subsequent data analysis process, as shown in Table 6.

Table 5. Transformation of column 'brand'.

Brand	Into	Brand
BCA		1
Mega		2
BRI		3
Mandiri		4
BNI		5
OCBC		6
Citibank		7
Permata		8
HSBC		9

Table 6. Transformation of 'region' column.

Region	Into	Region
Jakarta		1
Surabaya		2
Banjarmasin		3
Semarang		4
Bandung		5
Medan		6

5). The process of labeling the income and expenditure columns has been done to categorize users into Social Economic Status (SES) groups as shown in Table 7. Users are divided into four SES categories based on their spending level: SES A (>Rp5 million), SES B (Rp3-5 million), SES C (Rp1.5-3 million), and SES D/E (<Rp1.5 million). This categorization aims to facilitate a more in-depth analysis of users' behavior patterns and preferences based on their economic status.

Table 7. Labeling 'income' and result columns.

Income	Outcome	Into	SES
10000000	5500000		SES A
6000000	4000000		SES B
4500000	3500000		SES C
1200000	1000000		SES D/E

6). The credit card utility level has been categorized into three groups: low (5%-25%), medium (25%-50%), and high (>50%) as shown in Table 8. This division aims to facilitate a more structured analysis, allowing the identification of consumer behavior patterns in each utility group. This categorization helps in understanding how users with different usage levels behave and make decisions regarding their credit card usage.

Table 8. Transformation of 'utility_%' column.

Utility_%	Into	Utility_%
10		low
45		medium
55		high

3.4. Data Mining

This study analyzes the ads awareness patterns of credit card users using the K-means clustering method. The main objective is to identify user segments based on ads_awareness, ads_frequency, and brand, as well as additional demographic factors such as region, gender, age, education_level, income, outcome, and utility_%. The K-means algorithm is used to cluster the data, while the Silhouette Score determines the optimal number of clusters and evaluates the clustering results. Visualization of the results shows the distribution of users based on ad awareness and brand preference. The main parameters selected are ads_awareness, ads_frequency, and brand. This column was chosen because it plays an important role in influencing credit card usage patterns. Additional parameters such as \`region\`, \`gender\`, \`age\`, \`education_level\`, \`income\`, \`outcome\`, and \`utility_%\` were included to enrich the user segmentation analysis. The following are data mining steps to create a clustering model in this study:

1). Optimal Number of Clusters: The Elbow method is used to determine the optimal number of clusters by observing the change in Sum of Squared Errors (SSE). The optimal point is found when the decrease in SSE slows down, forming an “elbow” on the graph, which indicates the best number of clusters. In Figure 2, the graphical plots for each parameter used can be seen.

2). Clustering: Clustering of the dataset was performed with the K-Means algorithm using the optimal number of clusters determined through the Elbow method, which was 3 for the main parameters: utility, socioeconomic status, education level, age, and region, and 2 clusters for the gender parameter. The clustering process itself was run on the Google Colab platform using the Python programming language, as shown in Figure 3.

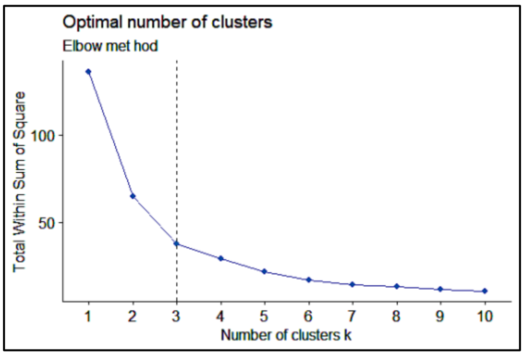
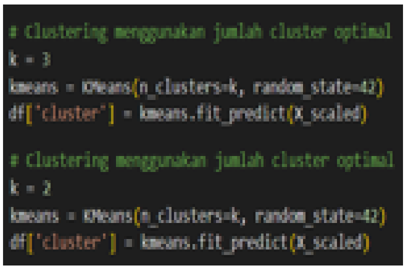


Figure 2. Result of Elbow method.



```
# Clustering menggunakan jumlah cluster optimal
k = 3
kmeans = KMeans(n_clusters=k, random_state=42)
df['cluster'] = kmeans.fit_predict(X_scaled)

# Clustering menggunakan jumlah cluster optimal
k = 2
kmeans = KMeans(n_clusters=k, random_state=42)
df['cluster'] = kmeans.fit_predict(X_scaled)
```

Figure 3. Python code for clustering.

3.5. Data Mining

The Silhouette Score for each parameter can be seen in Figure 4. The Silhouette Score measures the quality of grouping objects in a cluster by considering density and separability. The score ranges from -1 to 1, where a value of 1 indicates good clustering, 0 indicates objects are at the boundary between two clusters, and -1 indicates possible incorrect clustering.

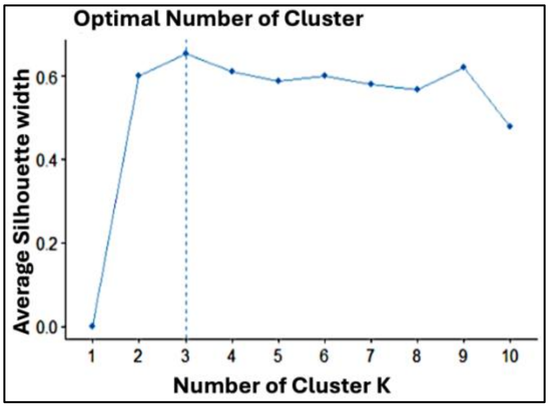


Figure 4. Silhouette Score Plot.

3.6. Interpretation and Implication

Interpretation of clustering results is an important stage in this research, providing insight into the advertisement awareness patterns of credit card users as well as providing implications to relevant stakeholders. The whole clusters are shown in Figure 5.

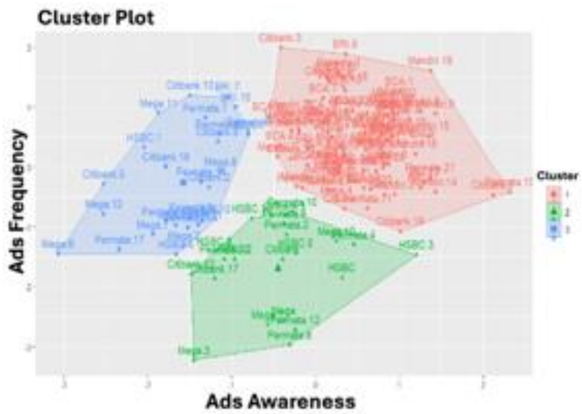


Figure 5. All cluster.

The visualization in Figure 5 resulted in several marketing strategies, namely, Cluster 1 (BCA, Mandiri, BRI, BNI) has high awareness and advertising frequency shown in Figure 6; it is recommended to increase advertising intensity to strengthen loyalty.

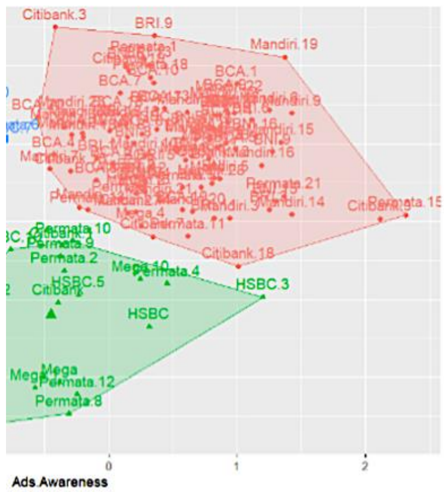


Figure 6. First cluster.

Cluster 2 (Mega, HSBC) as shown in Figure 7 shows moderate awareness and low frequency; strategies should focus on increasing frequency and effective media utilization.

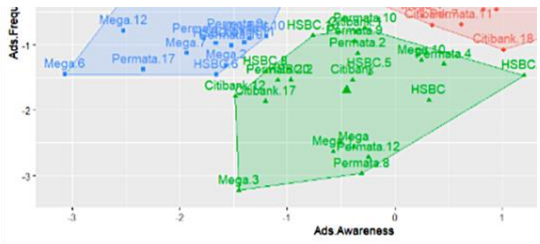


Figure 7. Second cluster.

Cluster 3 (Citibank, Permata) as shown in Figure 8 has low awareness but high frequency; need to revisit advertising strategy and improve message relevance.

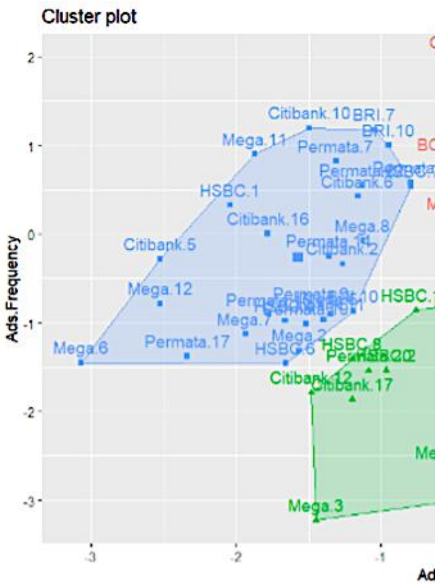


Figure 8. Third cluster.

Overall, Cluster 3 should optimize advertising, Cluster 2 increase frequency, and Cluster 1 maintain customer loyalty. These insights empower providers to shift from generic campaigns toward data-driven personalization and segmentation strategies, ensuring resource-efficient advertisement with greater customer engagement potential.

4. CONCLUSION

Based on the results of research on the advertisement awareness patterns of credit card users, it can be concluded that the K-Means algorithm is effective in grouping users based on advertisement awareness pattern, with silhouette score validation showing results >0.60 for main parameters, >0.20 for region, >0.30 for gender, >0.40 for age, >0.30 for education level, >0.60 for social economic status, and >0.30 for utility. The evaluation using Silhouette Score confirmed that the clustering results were valid and reliable, particularly in distinguishing users based on utility, SES, and education level. These findings highlight that advertisement awareness is influenced by a combination of personal characteristics and behavioral patterns rather than exposure frequency alone.

The implication of this study is clear; credit card providers must adopt more targeted and personalized advertising strategies that align with the awareness patterns of each user segment. Marketing approaches that consider user context—such as socio-economic status and digital media consumption habits—are more likely to enhance engagement and brand loyalty. This research thus contributes to the growing body of literature on data-driven marketing in the financial sector and demonstrates the practical utility of machine learning, particularly K-Means clustering, in customer segmentation.

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