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# A Comparative Analysis of K-Medoids and DBSCAN for Clustering Student Consumptive Behavior Profiles

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## ABSTRACT

The rapid adoption of digital payment technologies, such as e-wallets and mobile banking, has significantly altered the financial habits of university students, often blurring the psychological boundaries of spending compared to conventional cash transactions. This study aims to objectively map and cluster the multidimensional consumptive behavior profiles of university students based on their payment preferences and living status. A quantitative approach was employed using a dataset of 150 respondents evaluated across 15 financial and behavioral variables. To address the complexity of the high-dimensional data, preprocessing techniques including One-Hot Encoding, Min-Max Scaling, and Principal Component Analysis (PCA) were applied prior to modeling. The study utilized a comparative clustering approach to evaluate the performance of the K-Medoids and DBSCAN algorithms. The evaluation metrics demonstrate that DBSCAN ($\epsilon = 1.0$, MinPts $= 3$) outperformed K-Medoids, achieving an optimal Silhouette Score of 0.5438, a Davies-Bouldin Index of 0.7151, and a Calinski-Harabasz Index of 101.57. The DBSCAN model successfully mapped the data into six distinct consumer clusters. The profiling results reveal a significant behavioral divide: students preferring digital payments exhibit notably higher consumptive tendencies, impulsivity, and reliance on PayLater credit facilities compared to highly conservative cash users. Furthermore, living status dictates fixed expense allocations, compounding the financial vulnerabilities of specific groups. These empirical findings provide a robust data-driven foundation for developing targeted financial literacy strategies to help students manage digital financial ecosystems responsibly

Keywords: Consumptive Behavior, Clustering, DBSCAN, K-Medoids, Digital Payment.

## I. INTRODUCTION

In this digital era, payment technology innovations such as digital wallets (e-wallets), mobile banking, and the Quick Response Code Indonesian Standard (QRIS) have been massively adopted due to the convenience and efficiency they offer. Based on Bank Indonesia data, the adoption and volume of digital transactions in Indonesia continue to experience significant surges each year, reflecting a high public reliance on the digital financial ecosystem [1]. Nevertheless, conventional cash payment methods are in fact still maintained by a segment of society. This difference in transaction mediums between cash and cashless creates a variety of preferences that directly influence how university students manage their finances and fulfill

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their daily needs.

Various previous studies indicate that the type of payment instrument strongly influences a person's psychological barrier to spending, commonly known as the *pain of paying* [2]. In cash transactions, the direct release of physical money provides a more tangible awareness of expenditure. Conversely, the convenience of digital transactions often blurs these boundaries, making consumers less aware of their accumulated spending. Coupled with exposure to promotions such as discounts and cashback, this convenience is prone to triggering various levels of consumptive behavior and impulsive buying among university students.

Although the phenomenon of shifting transaction habits and its relationship to consumptive behavior has been widely discussed in previous literature (such as the findings by Puspitasari & Indrarini [3], Siregar et al. [4], and Pangaribuan et al. [2]), most prior studies tend to use linear causal analysis approaches merely to test the direct impact of payment methods on consumption levels. Studies that map the multidimensional clustering of financial behavior at the micro-level to view the consumer profile as a whole are still rarely found. Therefore, a data-driven approach is urgently needed to objectively identify and cluster university students' consumptive behavior profiles based on their transaction characteristics.

To address this gap, this study focuses on mapping student consumptive behavior profiles. A comparative approach is applied utilizing the K-Medoids algorithm, which is robust against outliers, and the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm, which is capable of identifying clusters based on data density and detecting spatial anomalies or noise [5]. Through the comparison of these two algorithms, this study is expected to produce comprehensive cluster modeling regarding students' financial behavior profiles, while also serving as an empirical foundation for formulating more adaptive financial literacy strategies.

## II. METHOD

This study was conducted using a quantitative approach, in which data will be analyzed to identify specific patterns within it. This approach was chosen to apply and compare two clustering algorithms K-Medoids and DBSCAN in objectively grouping data characteristics. This research was designed as a systematic workflow, comprising several structured stages ranging from primary data collection using purposive sampling, data preprocessing, implementation of clustering algorithms, to model evaluation and visualization of results. The following details the stages of the research conducted:

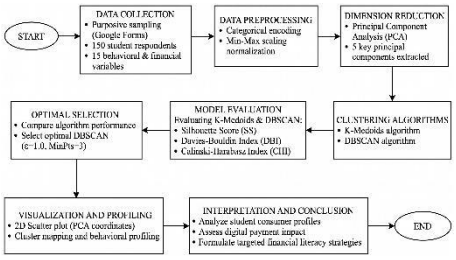


Figure 1. Research methodology flowchart

### *A. Data Collection*

Purposive sampling was used in this study to collect data on students financial habits and the payment methods they frequently use. The criteria established for this data collection specified the number of students from each faculty as follows: 45 students from the Faculty of Computer Science, and 15 students each from the Faculty of Medicine, the Faculty of Economics and Business, the Faculty of Law, the Faculty of Agriculture, the Faculty of Engineering, the Faculty of Architecture and Design, and the Faculty of Social and Political

Sciences. Data were collected through an online questionnaire using Google Forms, which included 15 research variables. Details of these variables are presented in Table 1.

TABLE I. DATA ATRIBUTE

| ID | Parameters | Description | Data Type |
|---|---|---|---|
| 1 | Age | The age of the student respondent. | Numeric |
| 2 | Income | The student's monthly income or pocket money allowance. | Numeric |
| 3 | Hangout Hours | The duration (in hours) spent hanging out or socializing within a certain period. | Numeric |
| 4 | Total Expenditure | The total overall expenses incurred by the student in a month. | Numeric |
| 5 | Non-Essential Expenditure | The amount of money spent on secondary or non-essential needs. | Numeric |
| 6 | Transportation Expenditure | The amount of money spent on transportation. | Numeric |
| 7 | Paylater Nominal | The total amount of debt or nominal usage from PayLater services. | Numeric |
| 8 | Online Shop Frequency | The number of times the student conducts online shopping transactions. | Numeric |
| 9 | Remaining Money | The leftover money or savings at the end of the month. | Numeric |
| 10 | Number of E-Wallets | The total number of active digital wallet (e-wallet) used by the student. | Numeric |
| 11 | Living Status | The student's living arrangement (Home and boarding or rented). | Categorical |
| 12 | Favorite Payment Method | The preferred payment method (e-wallet, m-banking, cash). | Categorical |
| 13 | PayLater Frequency | The frequency of using PayLater on a 1-5 Likert scale. | Ordinal |
| 14 | Impulsive Behavior | The impulsive buying tendency on a 1-5 Likert scale. | Ordinal |
| 15 | Shopping Regret | The post-purchase regret level on a 1-5 Likert scale. | Ordinal |

### *B. Data Preprocessing*

Data preprocessing was carried out to prepare the data for the next stage, which is clustering. The first step involved data transformation, specifically converting ordinal and categorical variables into numerical formats. For categorical data, such as living status and favorite payment method, the One-Hot Encoding technique was applied. This was necessary because the clustering algorithms rely on mathematical distance calculations that require numerical inputs.

In this stage, data normalization was also performed to adjust the scale of the data values.

Normalization is important because features with varying ranges such as monthly income measured in millions versus the number of active e-wallets can negatively affect the performance of the clustering model by dominating the distance calculations. The normalization technique used was the Min-Max Scaler. Min-Max Scaler transforms the data by scaling the features to a fixed range, typically between 0 and 1, using (1).

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where:

$x$ : Original Value

$x_{scaled}$ : Min-Max Scaled Value

$x_{min}$ : Minimum value of the feature

$x_{max}$ : Maximum value of the feature

### *C. Clustering Algorithms: K-Medoids and DBSCAN*

To objectively group and map the consumption behavior profiles of college students, this study applied two unsupervised learning algorithms with different characteristics: the K-Medoids algorithm and the DBSCAN algorithm.

1. K-Medoids Algorithm

   K-Medoids, or Partitioning Around Medoids (PAM), is a partition-based clustering algorithm that uses actual data points within a cluster (medoids) as cluster centers, making it more robust against outliers. The distance between data point $xi$ and medoid $vj$ is calculated using the *Euclidean distance* presented in (2).

$$d(xi, vj) = \sqrt{\sum_{m=1}^{d} (xim - vjm)^2} \quad (2)$$

   Explanation :

   *d(xi,vj)* : The distance between a data point and the cluster center (medoid)

   *m* : dimensional index

   *xim* : The value of the $i$-th data object for the $m$-th attribute

   *vjm* : The value of the $j$-th medoid at the $m$-th attribute

2. DBSCAN Algorithm

   DBSCAN is a density-based clustering algorithm. This algorithm automatically clusters nearby data points and assigns points in sparse areas or anomalies that do not meet the density criteria to the "noise" label (-1). The neighborhood of a data point is determined using the *Epsilon Neighborhood* presented in (3).

$$N_\epsilon(p) = \{q \in D \mid d(p,q) \leq \epsilon\} \quad (3)$$

   Explanation :

   $N_\epsilon(p)$ : The epsilon neighborhood of data point $p$

   $p$ : The core data point being evaluated

   $q$ : A neighboring data point within dataset *D*

   $d(p,q)$ : The distance between point $p$ and point $q$

   $\epsilon$ : The maximum search radius threshold (*Epsilon*)

### *D. Evaluation*

The clustering results can be evaluated using the silhouette score. This metric is calculated

by measuring the similarity of objects to their own cluster compared to neighboring clusters, resulting in a score ranging from -1 to 1. A value close to 1 indicates good clustering, while a value close to -1 indicates poor clustering [6]. The silhouette score is computed using the formula presented in (4).

$$s(i) = \frac{b(i)-a(i)}{\{a(i),b(i)\}} \quad (4)$$

Description :$s(i)$ : Silhouette score for data point

$a(i)$ : Average distance from point $i$ to all other points in the same cluster

$b(i)$ : Average distance from point $i$ to all points in the nearest neighboring cluster

Further evaluation can be performed using the Davies-Bouldin Index (DBI). This measure is obtained by comparing the degree of data dispersion within a cluster to the distance separating it from other clusters. A smaller DBI value or one closer to 0 indicates a well-defined cluster [7]. The formula for DBI calculation is provided in the referenced equation (5).

$$DB = \frac{1}{k}\sum_{i=1}^{k} \quad max_{j\neq i}\left(\frac{s_i+s_j}{d_{ij}}\right) \quad (5)$$

Description :

$k$ : Number of clusters

$si$ : Average distance between all points in cluster $i$ and the centroid of cluster $i$

$dij$ : Distance between the centroid of cluster $i$ and the centroid of cluster $j$

Next, an evaluation can be performed using the Calinski-Harabasz Index (CHI). This measure is obtained by comparing the degree of data dispersion between clusters with the degree of data dispersion within clusters. A higher CHI value indicates well-defined clusters with clear boundaries [7]. The CHI formula is presented in Equation (12).

$$CHI = \frac{Tr(Bk)/(k-1)}{Tr(Wk)/(n-k)} \quad (6)$$

Description :

$Tr(Bk)$ : Total between-cluster variance

$Tr(Wk)$ : Total within-cluster variance

$k$ : Number of clusters

$n$ : Total number of samples

## III. RESULT AND DISCUSION

Clustering analysis of students consumption behavior was conducted to map their financial behavior profiles. In addition, the use of two algorithms in this analysis K-Medoids and DBSCAN aimed to determine which algorithm could most effectively capture the variations in students behavioral profiles. This clustering analysis was performed using computational techniques, specifically the Python programming language with Google Colab as the supporting software.

The total dataset used in this study consisted of 150 respondents. All of this data was used in its entirety during the modeling phase without any data reduction. The variables used for clustering had different data types and measurement scales. These variables include categorical data processed using one-hot encoding, ordinal data measured using a Likert scale, and continuous numerical data in the form of monetary amounts in rupiah. The differences between Likert data and numerical data n the scales of these variables are shown in Table 2.

TABLE II. DESCRIPTIVE STATISTICS

| Parameters | Count | Mean | Median | Std | Min | Max |
|---|---|---|---|---|---|---|
| Age | 150 | 19,186 | 19 | 0,915 | 17 | 22 |
| Income | 150 | 1.224.000 | 150 | 150 | 150 | 150 |
| Hangout Hours | 150 | 3 | 1,87 | 0 | 7 | 2,95 |
| Total Expenditure | 150 | 800.000 | 536.753,00 | 60.000 | 2.125.000 | 893.320 |
| Non-Essential Expenditure | 150 | 275.000 | 212.455,97 | 15.000 | 900.000 | 306.100 |
| Transportation Expenditure | 150 | 112.900 | 100.580,52 | 0 | 393.125 | 149.130,33 |
| Paylater Nominal | 150 | 0 | 41.003,96 | 0 | 250.000 | 12.133,33 |
| Online Shop Frequency | 150 | 1 | 0,79 | 1 | 3 | 1,59 |
| Remaining Money | 150 | 200.000 | 180.516,41 | 0 | 643.750 | 199.945 |
| Number of E-Wallets | 150 | 3 | 1,25 | 1 | 8 | 2,85 |
| PayLater Frequency | 150 | 0,14 | 0 | 0,492 | 0 | 3 |
| Impulsive Behavior | 150 | 2,726 | 3 | 1,111 | 1 | 5 |
| Shopping Regret | 150 | 3,426 | 4 | 1,058 | 1 | 5 |

Based on Table 2, it is clear that the numerical variables used in this study have a wide range of scales. Observation values range from single digits and the tens (such as in the variables of frequency, hours spent hanging out, and the behavioral Likert scale) to hundreds of thousands and millions (such as in the variables of spending, remaining money, and income). These significant differences in scale can negatively impact the performance of clustering algorithms based on mathematical distance calculations, as variables with large value ranges will dominate those with smaller scales.

Therefore, a data normalization step is absolutely necessary before the clustering process. The technique used is the Min-Max Scaler, which transforms all numerical feature values into a fixed range, specifically between 0 and 1. Selecting this method is crucial to ensure that the scale of the numerical data aligns with the two categorical variables that were previously converted using the One-Hot Encoding technique (which also produces binary values of 0 and 1), so that each feature has a balanced weight and contribution within the model.

Furthermore, since combining the numerical variables with the One-Hot Encoding results in a large number of feature dimensions, the clustering algorithm is prone to a decline in performance due to the curse of dimensionality. To address this complexity, a dimension reduction technique using Principal Component Analysis (PCA). PCA aims to reduce the number of variables by summarizing essential information and preserving the maximum variance of the original data into a smaller number of principal components. A summary of the results of the dimension reduction using PCA is shown in Table 3.

TABLE III. PRINCIPAL COMPONET ANALYST (PCA) VARIANCE EXPLAINED

| Principal Component | Variance Explained (%) | Cumulative Variance (%) |
|---|---|---|
| PC1 | 29.39 | 29.39 |
| PC2 | 20.56 | 49.95 |

| | | |
|---|---|---|
| PC3 | 10.51 | 60.46 |
| PC4 | 9.38 | 69.84 |
| PC5 | 6.47 | 76.31 |

Based on Table 3, the dimensionality reduction process yielded five significant principal components (PCs). The first principal component (PC 1) dominates by explaining 29.39% of the data variance, followed by PC 2 with 20.56%. Cumulatively, these five principal components account for 76.31% of the total variance in the original dataset. This cumulative value indicates that the five components are sufficiently representative to capture the primary information patterns from the initial variables, while effectively reducing the computational complexity for the subsequent clustering stage.

### *A. Clustering Algorithm Evaluation*

Following the pre-processing stage, the K-Medoids algorithm was tested across a range of $k$ values (2 to 6), while DBSCAN was evaluated using various combinations of the search radius ($\epsilon$) and minimum samples (*MinPts*) parameters. The clustering quality of both algorithms was assessed using three internal validity metrics: the Silhouette Score, Davies-Bouldin Index (DBI), and Calinski-Harabasz Index (CHI). The summary of the K-Medoids evaluation results is presented in Table 4, whereas the DBSCAN evaluation results are detailed in Table 5.

TABLE IV. K-MEDOIDS ALGORITHM EVALUATION RESULT

| $k$ Value | **Silhoette Score** | **DBI** | **CHI** |
|---|---|---|---|
| 2 | 0.3647 | 1.2560 | 84.73 |
| 3 | 0.2376 | 1.9080 | 54.86 |
| 4 | 0.1550 | 2.1289 | 26.35 |
| 5 | 0.1474 | 2.0844 | 22.68 |
| 6 | 0.3835 | 1.0039 | 66.02 |

TABLE V. DBSCAN ALGORITHM EVALUATION RESULT

| **Eps(ϵ)** | **Min Samples** | **Jumlah Klaster** | **Total Noise (-1)** | **Sihouette Score** | **DBI** | **CHI** |
|---|---|---|---|---|---|---|
| 1,0 | 3 | 6 | 0 | 0,5438 | 0,7151 | 101,57 |
| 0,7 | 3 | 6 | 1 | 0,5199 | 0,6535 | 86,23 |
| 0,5 | 3 | 6 | 7 | 0,5130 | 1,3202 | 75,34 |
| 0,3 | 3 | 14 | 25 | 0,2745 | 1,2672 | 27,87 |

After conducting several trials across various parameter configurations, the optimal clustering performance for both algorithms was successfully identified. Table 6 presents a direct comparison of the best evaluation scores achieved by K-Medoids and DBSCAN.

TABLE VI. COMPARISON OF OPTIMAL CLUSTERING PERFORMANCE

| **Algorithm** | **Optimal Parameter** | **Cluster** | **SS** | **DBI** | **CHI** |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| K-Medoids | $k = 6$ | 6 | 0.3835 | 1.0039 | 66.02 |
| DBSCAN | $\epsilon = 1,0$ ; Min = 3 | 6 | 0,5438 | 0,7151 | 101,57 |

The comparison clearly highlights a significant performance gap between the two algorithms; although both methods ultimately identified 6 distinct clusters, DBSCAN emerged as the vastly more effective method for analyzing this dataset. By achieving a superior Silhouette Score of 0.5438 alongside a low Davies-Bouldin Index of 0.7151, this algorithm successfully formed highly cohesive groups with minimal overlap. This structural quality is further reinforced by a strong Calinski-Harabasz value of 101.57, which ensures an optimal variance distribution across the groups. Consequently, running the DBSCAN algorithm with $\epsilon = 1,0$ ; Min = 3 proved to be the most reliable and accurate approach for profiling the students' consumptive behaviors and payment preferences.

### *B. Visualization and Cluster Profiling*

To provide a clearer understanding of how the student consumptive behavior profiles are distributed, the clustering results generated by the DBSCAN algorithm are projected into a two-dimensional space. Figure 2 illustrates a scatter plot visualization of the optimal DBSCAN clusters, using the first two principal components (PC 1 and PC 2) as the coordinate axes.

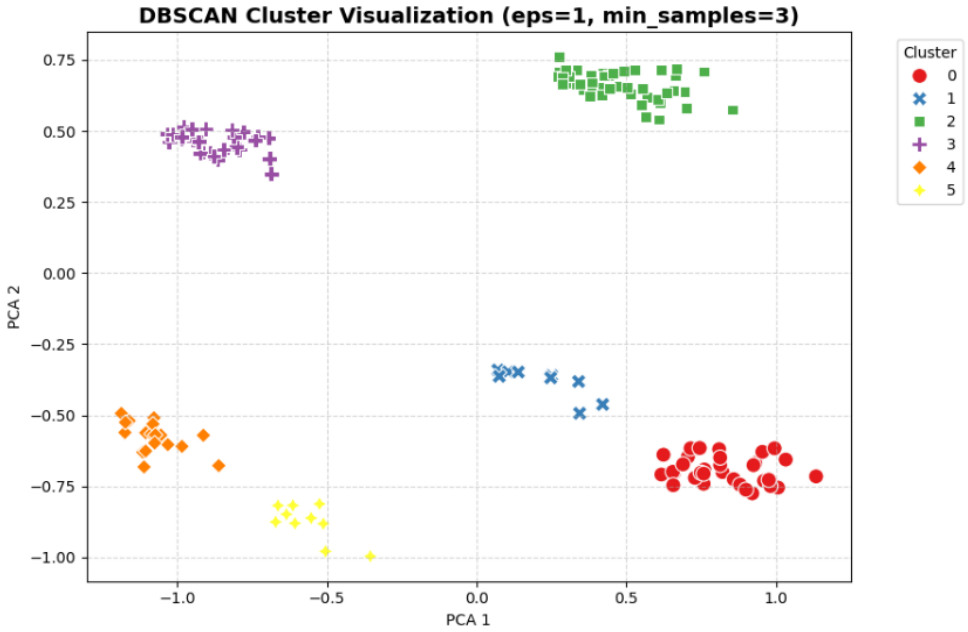


Figure 2. Scatter plot visualization of DBSCAN clustering results.

As illustrated in Figure 2, the projection of the dataset onto the first two principal components reveals the formation of six distinct clusters, alongside several scattered data points identified as noise (-1). The spatial distribution in this two-dimensional plane highlights how the DBSCAN algorithm effectively groups students with similar consumptive patterns while isolating extreme outliers that do not conform to the general density. Because PC 1 and PC 2 account for a significant portion of the total variance, this visual representation serves as a reliable indicator of the structural separation within the complex, high-dimensional data.

Although the scatter plot confirms the structural validity of the clustering results, a deeper

analysis is required to interpret the practical meaning of each group. To achieve this, a profiling process was conducted by mapping the clustered data back to its original variables and calculating the central tendencies (mean values). By evaluating variables such as total expenditure, e-wallet usage, impulsive behavior, and PayLater nominals within each specific group, the unique behavioral characteristics and payment preferences of every segment can be clearly defined. The detailed profiling results for all six clusters are systematically summarized in Table 7.

TABLE VII. CLUSTER PROFILING

| Parameters | Cluster 0 | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 |
|---|---|---|---|---|---|---|
| Age | 18,97 | 19,33 | 19,39 | 19,30 | 18,89 | 19 |
| Income | 1,648,484.85 | 1,155,555.56 | 1,346,326.53 | 908,333.33 | 802,631.58 | 1,030,000.00 |
| Hangout Hours | 3.06 | 2.11 | 2.80 | 3.17 | 2.95 | 3.40 |
| Total Expenditure | 1,302,272.73 | 694,444.44 | 1,020,612.24 | 668,333.33 | 453,315.79 | 610,000.00 |
| Non-Essential Expenditure | 348,636.36 | 280,000.00 | 337,346.94 | 264,333.33 | 230,526.32 | 305,000.00 |
| Transportation Expenditure | 135,664.39 | 136,666.67 | 137,553.57 | 167,645.83 | 179,111.84 | 149,000.00 |
| Paylater Nominal | 10,757.58 | 22,222.22 | 3,775.51 | 20,000.00 | 25,263.16 | 0.00 |
| Online Shop Frequency | 1.64 | 1.33 | 1.73 | 1.40 | 1.74 | 1.30 |
| Remaining Money | 257,500.00 | 244,861.11 | 189,040.82 | 140,791.67 | 200,000.00 | 200,375.00 |
| Number of E-Wallets | 2.97 | 2.33 | 3.06 | 2.90 | 2.32 | 2.80 |
| PayLater Frequency | 0.15 | 0.00 | 0.16 | 0.20 | 0.05 | 0.10 |
| Impulsive Behavior | 2.79 | 2.44 | 2.63 | 3.00 | 2.42 | 3.00 |
| Shopping Regret | 3.09 | 3.56 | 3.61 | 3.47 | 3.47 | 3.30 |
| Living Status | Boarding / Rented House (100%) | Boarding / Rented House (100%) | Boarding / Rented House (100%) | House (100%) | House (100%) | House (100%) |
| Favorite Payment Method | Mobile Banking (100%) | Cash (100%) | E-Wallet (100%) | E-Wallet (100%) | Cash (100%) | Mobile Banking (100%) |

Based on the profiling results in Table VII, the six clusters reveal distinct consumer behaviors driven by living status and payment preferences. Among boarding house students, Cluster 0 (Mobile Banking) exhibits the highest income and expenditure while maintaining financial stability. Conversely, Cluster 1 (Cash) represents highly conservative spenders with low total expenditure and high shopping regret, whereas Cluster 2 (E-Wallet) shows active digital consumption accompanied by the highest post-purchase guilt.

For students living at home, the patterns differ significantly. Cluster 3 (E-Wallet) displays the highest impulsive behavior and reliance on PayLater, indicating financial vulnerability. In contrast, Cluster 4 (Cash) focuses strictly on basic needs like transportation and avoids impulsive purchases. Lastly, Cluster 5 (Mobile Banking) is highly social with the most hangout hours, yet manages finances well without digital debt. Overall, the data indicates that digital payment users generally exhibit higher consumptive tendencies and impulsivity compared to cash users, while living status dictates fixed expenditure allocations.

## IV. CONCLUTION

This study successfully mapped the consumptive behavior profiles of university students based on their transaction characteristics and living status. A comparative analysis between two unsupervised learning algorithms revealed that DBSCAN significantly outperformed K-Medoids in handling this multidimensional dataset. By utilizing the optimal parameters of $\epsilon = 1.0$ and $\text{MinPts} = 3$, DBSCAN produced superior internal validity metrics, achieving a Silhouette Score of 0.5438, a Davies-Bouldin Index of 0.7151, and a Calinski-Harabasz Index of 101.57. These scores indicate that the algorithm successfully formed highly cohesive and well-separated clusters.

Through the DBSCAN model, the students' financial behaviors were grouped into six distinct consumer profiles. The profiling analysis explicitly demonstrates that the type of payment instrument strongly influences a student's psychological barrier to spending. Students who primarily utilize digital payment methods particularly e-wallets and mobile banking consistently exhibit higher consumptive tendencies, increased non-essential spending, and greater impulsivity compared to those who rely on conventional cash. Furthermore, digital payment users display a concerning vulnerability to digital debt, as evidenced by a higher reliance on PayLater facilities. Conversely, students utilizing cash transactions maintain strict, needs-based financial prioritization accompanied by a higher degree of post-purchase caution.

Ultimately, these findings empirically prove that the convenience of digital and cashless transactions significantly accelerates consumptive behavior among students. The results of this study offer a valuable data-driven foundation for educational institutions and financial policymakers to formulate targeted financial literacy programs. Such initiatives are crucial to educating students on how to mitigate the risks of impulsive buying and manage their finances adaptively within the modern digital financial ecosystem.

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