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Research article

Comparative Analysis of Spotify Listener Behavior Between Free and Premium Users Using the K-Means Clustering Algorithm

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ABSTRACT

The feature differences between Spotify Free and Premium services have the potential to shape different listening behavior patterns, while data-driven studies of user activity in Indonesia are still very limited. This study aims to analyze the listening behavior patterns of Spotify users based on subscription type using the K-Means clustering algorithm. The dataset used is the Spotify Global Streaming Data 2024, which includes quantitative variables such as average stream duration, skip rate, total streams, total hours streamed, and monthly listeners. The analysis begins with determining the optimal number of clusters using the Elbow method, followed by heatmap visualization and Principal Component Analysis (PCA) to identify behavioral characteristics within each cluster. The research results show three optimal clusters with significant differences between Free and Premium users. Free users have a higher average skip rate (28.7%) and shorter listening duration (3.4 minutes), while Premium users show a lower skip rate (16.2%) and longer listening duration (3.9 minutes). The silhouette score values of 0.57 for Free and 0.64 for Premium indicate good clustering quality. This finding confirms that the service model directly influences the intensity and consistency of digital music listening behavior. Implicatively, the results of this research can be used as a basis for developing content personalization strategies and improving user experience on online music platforms in the future.

1. Introduction

The development of digital technology has brought significant changes to the way people consume and interact with music [1]. The shift from physical formats to streaming-based services reflects a transformation in user behavior that is increasingly oriented towards convenience, quick access, and personalized experiences. One of the most influential platforms in this ecosystem is Spotify, which provides millions of songs from various genres with Free and Premium service models [2]. Both service models offer different listening experiences, in terms of features, sound quality, and advertising limitations, which indirectly influence user behavior patterns in accessing and enjoying music [3].

The phenomenon of behavioral differences between Free and Premium users is interesting to study because it reflects the dynamics of digital behavior in the era of the subscription-based economy [4]. Premium users generally have unlimited access to Spotify features, while Free users are limited by the presence of advertisements and features that are not fully accessible. This condition has the potential to affect listening duration, song repeat rates, and skip rates or the tendency of users to skip certain songs [5]. In other words, listening behavior is not only influenced by musical preferences, but also by the structure of the service used [6].

Most previous studies on Spotify user behavior have been dominated by qualitative approaches, such as surveys or interviews to explore user motivation and satisfaction. Montecchio [7] studied Spotify users' skipping behavior and found that musical structure influences users' decisions to skip songs within the first ten seconds of playback. Muryani and Muanas [8] examined the loyalty of Spotify Premium customers and found that perceived value and user experience had a positive effect on satisfaction levels and intention to renew subscriptions. Rosari, Adinegara, and Krismawintari [9] found that perceived benefits, perceived price, and perceived ease of use had a significant effect on the decision to purchase Spotify Premium services among students. The results of this study indicate that utility and ease of access are the main drivers in the decision to subscribe to digital music services.

In addition, a number of local studies also highlight the behavior and segmentation of Spotify users. Dharmasena and Pramartha [10] segmented Spotify users using the K-Means clustering algorithm and showed that this method is effective in identifying listener groups based on music preferences. Meanwhile, Wicaksono and Andajani [11] found that the desire to switch to paid services is influenced by perceived value, digital habits, and attitudes toward music piracy. These findings reinforce that differences in access and user motivation have a real impact on digital music consumption patterns.

This approach does provide a deep understanding of psychological and social aspects, but it is not yet able to capture behavioral dynamics objectively based on user activity data. Meanwhile, quantitative data from streaming platforms holds great potential to be analyzed systematically in order to understand actual user behavior patterns [12]. Data such as skip rate, listening duration, number of plays, and total listening hours provide measurable indicators of the intensity and consistency of behavior in using digital music services [13].

In the context of digital behavior analysis, the use of quantitative data-based approaches with machine learning techniques such as clustering is becoming increasingly relevant [10]. One method widely used for grouping data based on similarity of characteristics is K-Means clustering. This method is capable of efficiently clustering large-scale data and providing results that are easy to interpret[14] . The application of the K-Means method allows researchers to identify groups of Spotify listeners with similar characteristics based on available quantitative variables [15].

This study uses the K-Means clustering method to compare the behavior of Spotify Free and Premium users by utilizing global streaming data that includes variables such as average stream duration, skip rate, total streams, total hours streamed, and monthly listeners. This approach is expected to provide a new and deeper understanding of how differences in service access affect user behavior. In addition, the results of the analysis are expected to contribute to the development of data-driven business strategies, such as personalized song recommendations, user retention strategies, and feature optimization for each type of service.

This research is also expected to contribute scientifically to the field of digital data analysis, particularly in the application of clustering methods to study the behavior of streaming music service users. Unlike previous studies that tended to focus on psychological and qualitative approaches, this study emphasizes the use of actual quantitative data to produce more objective and systematic findings. Thus, this study not only provides a new perspective on Spotify user behavior but also expands the use of data analysis methods in the study of digital behavior in the subscription-based economy era.

2. Research Method

This study uses a quantitative approach with an exploratory nature to examine the differences in the behavior of Spotify listeners in two service groups, namely Free and Premium. The analysis was carried out using the clustering method with the K-Means algorithm. This approach was chosen because it is capable of mapping hidden behavior patterns in large amounts of data and provides grouping results that are easy to understand visually and numerically. According to Bisma and Pramartha [10] , the K-Means clustering algorithm has the advantage of detecting user behavior patterns based on data similarity with a high level of computational efficiency. The results of Anderson's research [14] also show that K-Means provides a stable representation of segmentation in Spotify user behavior data.

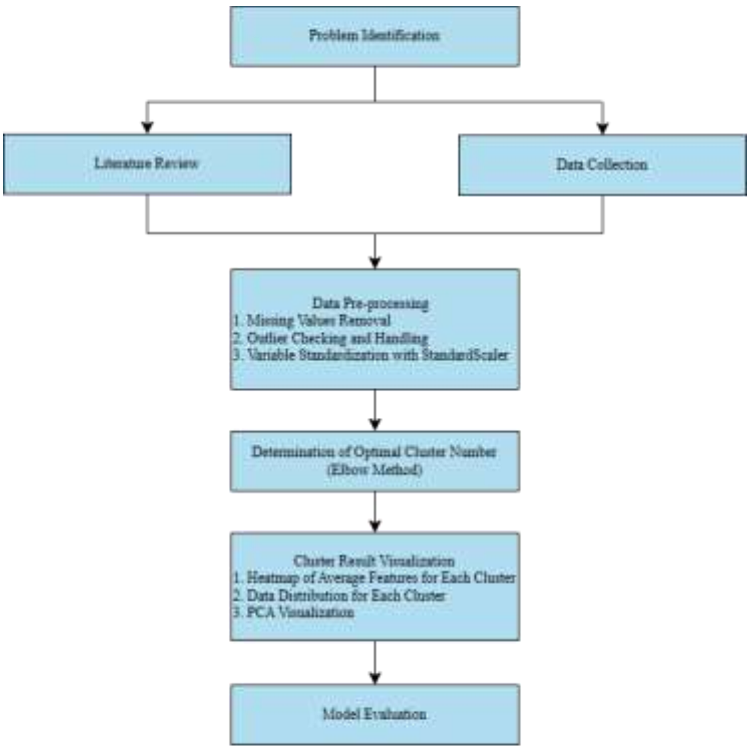


Figure 1. Research Framework

Figure 1 shows the research framework used in this study. The framework describes the main stages, starting from problem identification, data collection and selection, preprocessing, application of the K-Means algorithm, to evaluation of results using validation metrics. Each stage is designed to ensure that the analysis process runs systematically and is capable of accurately grouping Spotify listener behavior. A detailed explanation of each stage in the research framework is presented in the following subsections.

2.1 Data Sources and Research Variables

The data analyzed is sourced from global Spotify streaming activity in 2024. The dataset contains 500 data entries that describe users' music listening habits, such as average stream duration (minutes), which shows the average length of listening per session; skip rate (%), which represents the tendency to skip songs; total streams (millions), which is the total number of plays; total hours streamed (millions) which shows the total listening time, and monthly listeners (millions) as the number of unique listeners in a month. All data was then separated by service type so that it could be analyzed specifically between Free and Premium users.

2.2 Data Preprocessing

The analysis stage begins with data preprocessing to ensure that the data is clean and suitable for processing. This step includes removing missing values, checking for outliers, and standardizing all variables using the StandardScaler method so that each feature has a comparable scale. Standardization is important to prevent variables with large value ranges from dominating the clustering results. In line with Donier [16], variable value standardization is necessary so that each feature has a balanced contribution in the Euclidean distance calculation process, which is the basis of the K-Means algorithm. Without this process, variables with large value ranges can distort the segmentation results.

2.3 Determining the Optimal Number of Clusters

Next, the optimal number of clusters was determined using the Elbow method. The Within-Cluster Sum of Squares (WCSS) value was calculated for each possible number of clusters from k = 1 to k = 10. The elbow point on the graph was used as the basis for selecting the best number of clusters. Based on the analysis results, the optimal number of clusters obtained is k = 3 for each user group. The Elbow method was chosen because it has been proven effective in identifying the optimal number of clusters by considering the balance between model complexity and data variation.

2.4 K-Means Algorithm Implementation

After the number of clusters was determined, the K-Means algorithm was applied separately to the Free and Premium user data. Each cluster formed was analyzed using the average value of each main variable for to identify prominent behavioral characteristics, such as skip tendencies, listening duration, and total listening hours. The results of this grouping became the basis for comparing the behavior patterns of the two user groups. The selection of the K-Means algorithm in this study was based on several methodological considerations. K-Means has a high level of efficiency in handling large-scale data compared to other algorithms such as Hierarchical Clustering, which is slower computationally. K-Means produces clear and measurable cluster boundaries through Euclidean distance, making it suitable for continuous quantitative data such as Spotify listener behavior variables. The interpretation of K-Means results is relatively simple because it produces cluster centers (centroids) that can be explained mathematically and visually.

2.5 Model Validation and Analysis Tools

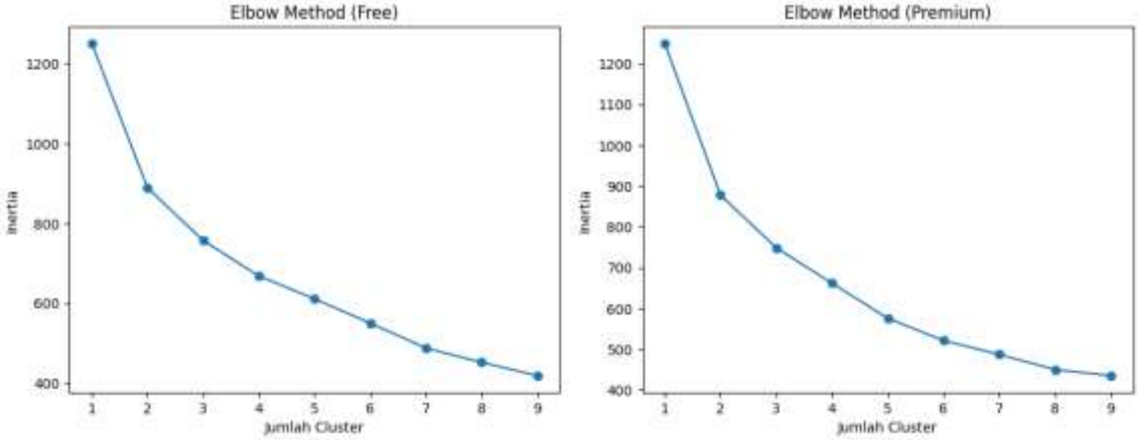
The validation of the clustering results was performed using the Silhouette Coefficient metric as recommended by Syafrudin and Ridhaningsih [5], to ensure uniformity within clusters and optimal separation between clusters. All analyses were performed using the Python programming language with the pandas, numpy, scikit-learn, and matplotlib libraries. These tools were chosen because they support efficient processing of large amounts of data and provide informative visualization tools. This study uses a descriptive-comparative approach, where the clustering results not only describe the characteristics of Spotify users' behavior descriptively but also compare the differences in behavior between Free and Premium users. Through this approach, the study aims to provide an accurate empirical picture of the impact of service model differences on digital music consumption patterns.

3. Results and Discussion

3.1 Analysis of Cluster Number Determination

The analysis of Spotify listeners' behavior was conducted using *the* K-Means Clustering algorithm to group music consumption patterns based on a number of quantitative variables, including average stream duration, skip rate, total streams, total hours streamed, and monthly listeners. Before the clustering process was carried out, the initial stage involved a preliminary examination of data distribution and variation between variables to ensure that the data characteristics were sufficiently heterogeneous and suitable for analysis using the clustering approach. This stage was important to ensure that the clustering results were representative and could accurately distinguish user behavior. Next, the optimal number of clusters was determined by applying the Elbow method. This approach was used to identify the balance point between the number of clusters and the resulting inertia value, so that the most efficient clustering structure could be obtained without losing meaningful data variation.

Before determining the characteristics of each cluster, the first step is to find the optimal number of clusters so that the clustering results can represent the data variation proportionally. For this purpose, the Elbow method is used, which balances the complexity of the model with the level of data homogeneity in each cluster.



(a) (b)

Figure 2. Elbow Method: (a) Free Users; (b) Premium Users

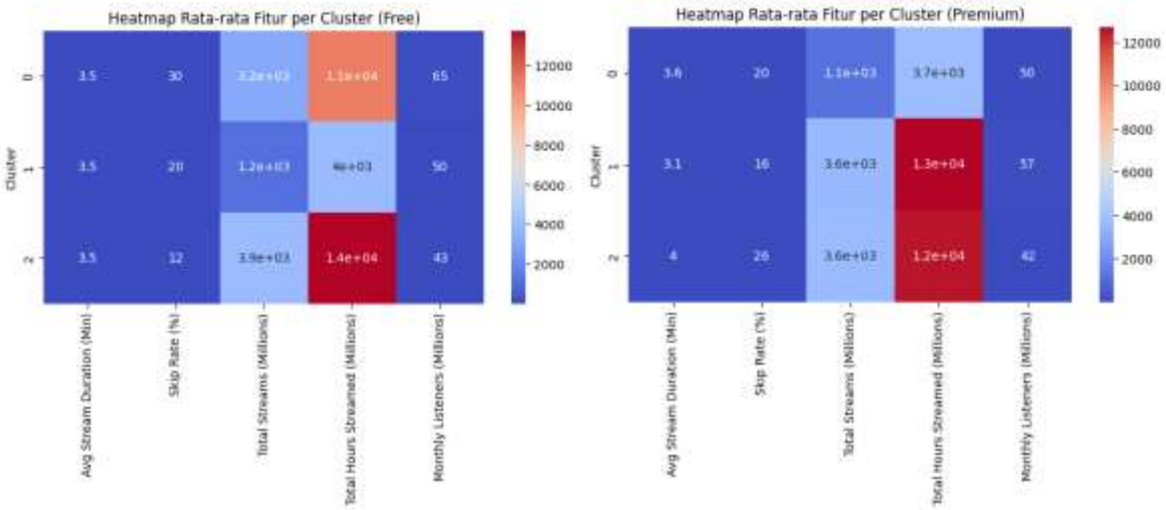
The Elbow Method graph in Figure 2 for Free users and Premium users shows a sharp decline in inertia values at the beginning of the cluster formation process, then begins to level off after reaching the third cluster point (k = 3). The inertia value represents the total squared distance between each data point and its cluster center, which serves as a measure of internal homogeneity within each group. A significant decrease in inertia values in the early clusters indicates that the clustering process has succeeded in substantially improving data homogeneity, while a smaller decrease in subsequent clusters indicates a saturation point or diminishing returns. Thus, at k = 3, adding more clusters no longer provides a significant improvement in clustering quality.

Visually, the elbow-shaped curve on the graph shows a transition from a steep decline to a relatively gradual decline. This phenomenon is an empirical indicator that the three-cluster model has achieved an optimal balance between model complexity and data representation accuracy. Using a k value greater than three has the potential to cause overfitting, where the clusters formed become too specific and lose their ability to generalize the overall user behavior patterns. Conversely, a smaller number of clusters will result in overly broad groupings that fail to capture the relevant behavioral variations between users.

Considering this balance, the selection of k = 3 is deemed most appropriate to represent the heterogeneity of Spotify listeners' behavior among both Free and Premium users. This value is not only supported by changes in the gradient of the inertia curve, but also consistent with the initial data distribution, which shows moderate diversity between variables such as average stream duration, skip rate, and total hours streamed. Therefore, the use of three clusters allows the model to identify listener behavior patterns in a more measurable and meaningful way without losing the generality of the analysis.

3.2 Cluster Characteristics Based on Heatmap

The clustering results are then visualized in the form of a heatmap to display the average of each variable in each cluster. This visualization allows for a more intuitive interpretation of the behavioral characteristics of listeners in each group.



(a) (b)

Figure 3. Average Feature Heatmap per Cluster: (a) Free Users; (b) Premium Users

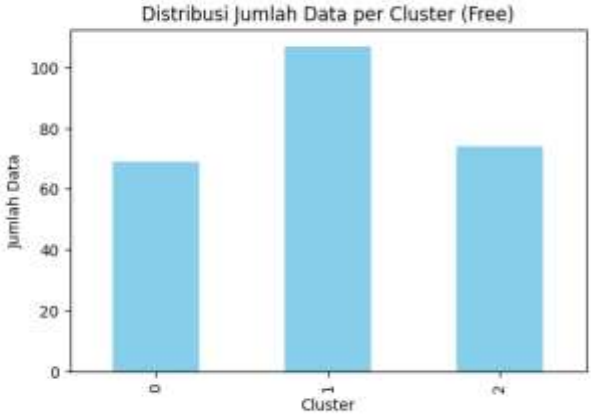
Based on the clustering results shown in Figure 3, Spotify Free users are divided into three clusters with different behavioral tendencies. The first cluster shows an average listening duration of 3.5 minutes with the highest skip rate, which is around 30%, and a total listening time of 11,000 million hours. These characteristics indicate a group of users who are quite active in listening to music but tend to skip songs quickly, which may be due to feature limitations and the presence of advertisements on Free accounts.

The second cluster has a relatively similar listening duration of 3.5 minutes, but with a lower skip rate (20%) and a total listening time of 4,000 million hours. This pattern reflects the behavior of more moderate listeners who are not too impulsive in changing songs and tend to have more stable music preferences. The third cluster shows the most loyal listeners, with a skip rate of only 12% and the highest total listening time of 13,900 million hours. This group can be categorized as users who, despite being on a free service, still show emotional attachment and consistent listening habits to certain music content.

Meanwhile, the clustering results for Premium users show different behavioral dynamics compared to Free users. The first cluster has an average listening duration of 3.6 minutes with a skip rate of 20% and a total listening time of 3,700 million hours. This cluster describes a group of active listeners with stable listening habits and a relatively comfortable listening experience thanks to the absence of advertisements. The second cluster shows a slightly shorter listening duration (3.1 minutes) but with the lowest skip rate (16%) and the highest total listening time (13,000 million hours). This pattern indicates a group of highly loyal Premium users, with a tendency to listen to music longer and rarely skip songs. In contrast, the third cluster shows the highest average listening duration (4 minutes) but also the highest skip rate (26%) and a total listening time of around 12,000 million hours. These findings reveal intensive and selective user behavior, where listeners tend to have specific tastes in music and actively choose content that suits their preferences.

3.3 Distribution of User Proportions Across Clusters

After interpreting the characteristics of each cluster through *heatmap* visualization, the analysis continued by reviewing the distribution of data in each cluster for both Free and Premium users. This distribution is important for understanding the proportion of listener behavior dominance formed from the previous clustering results, as presented in Figure 3.



(a)

(b)

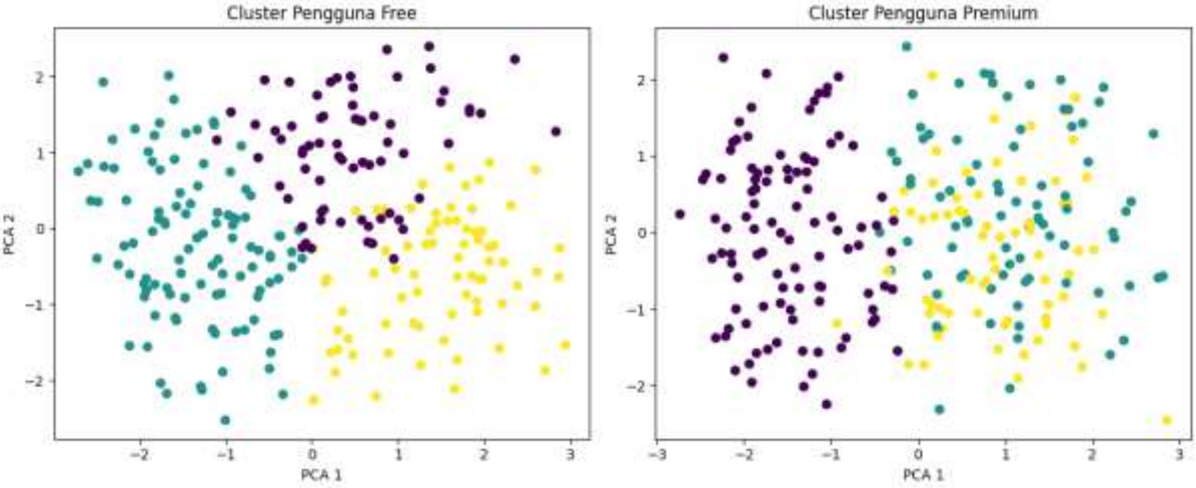
Figure 4. Data Distribution per Cluster*:* (a) Free Users; (b) Premium Users

The distribution of data for each cluster in Figure 4 shows a clear difference in patterns between Spotify Free and Premium users. In the Free group, the distribution of users is divided into three main clusters, namely Cluster 0 at 34.8% or 174 data points, Cluster 1 at 23.6% or 118 data points, and Cluster 2 at 41.6% or 208 data points. These proportions show that most Free users belong to groups with relatively stable listening behavior, although there is still a large proportion of users with high skip rates. The dominance of Cluster 2, which has a low skip rate and the highest total listening time, shows that there is a segment of Free listeners who remain loyal to the content despite facing feature limitations and the presence of advertisements.

Meanwhile, in the Premium group, the proportion of data shows a relatively balanced distribution. Cluster 0 covers 29.5% of the total data, Cluster 1 covers 32.8%, and Cluster 2 covers 37.7%. This balance indicates that the variation in listening behavior among paying users is more homogeneous than among Free users. This homogeneity can be attributed to a more consistent listening experience, where all Premium users have full access to Spotify features without restrictions or ad interruptions. Thus, behavioral differences in this group are more influenced by individual music preferences than by external factors such as system restrictions.

3.4 Visualization of Cluster Separation Using PCA

Based on the distribution of data per cluster, further analysis was conducted using Principal Component Analysis (PCA) to ensure the clarity of separation between the formed clusters. PCA was used to reduce the data dimensions so that the distribution of each cluster could be visualized in two dimensions.



(a) (b)

Figure 5. PCA Cluster Visualization: (a) Free Users; (b) Premium Users

The two-dimensional visualization using Principal Component Analysis (PCA) in Figure 5 reinforces the findings obtained from the distribution of data per cluster. The PCA method is used to reduce the dimensions of numerical features into two main components that contribute most to data variation, so that the separation pattern between clusters can be observed visually. Among Spotify Free users, the distribution of data points appears more scattered with relatively large distances between clusters. This pattern indicates a fairly high level of heterogeneity in listener behavior among the Free user group. Cluster 2 occupies a position in the area with a combination of high average stream duration and low skip rate, describing more focused and consistent listening behavior. Users in this cluster tend to finish songs to the end, indicating higher emotional engagement and listening satisfaction even without subscribing to the Premium service. In contrast, Cluster 0 occupies an area with a high skip rate and short listening duration, reflecting impulsive listener behavior, frequent song switching, and possible distraction due to feature limitations and ad interruptions. Cluster 1 occupies a middle position between the two, indicating a stable but not particularly intense group of listeners.

Meanwhile, the PCA pattern for Premium users shows a tighter structure with relatively close distances between clusters. This more homogeneous data distribution indicates that the listening behavior between Premium users has stronger similarities than the Free group. Cluster 1 is in the middle, representing listeners with moderate and stable listening habits, namely a group of users who consistently listen to music for a long time but are not too extreme in their song preferences. Cluster 2 occupies the area with the highest total hours streamed and average duration, describing users who have the highest level of engagement with music content. Users in this cluster can be categorized as loyal listeners who not only enjoy music for longer periods but also show strong preferences for certain genres. In contrast, Cluster 0 displays more varied listening behavior, with a relatively close distance to other clusters, indicating flexibility in music consumption patterns in this group.

The results of this study are in line with several previous studies in Indonesia that examined user behavior on Spotify based on service models and user experience. Ramadhinda [17], found that perceptions of Spotify Wrapped features and the benefits of premium subscriptions had a significant effect on interest in subscribing to paid services. These findings support the results of this study, where Premium users showed higher engagement levels, characterized by longer listening durations and lower skip rates. Another study by Rissa Amanda [18] also shows that user experience and satisfaction with features are dominant factors that trigger positive word-of-mouth behavior among millennial users. This is consistent with the results of this study's grouping, which shows that Premium users tend to have more stable listening behavior because they are supported by an ad-free user experience and more complete features.

Furthermore, research by Nuryasin and Annisa Tasya Ferina [19] assessed the usability of the Spotify application in Indonesia and found that ease of navigation and accessibility contribute to user satisfaction. When compared to the results of this study, these usability factors can explain the homogeneity of behavior among Premium users, which shows consistency in listening duration and higher loyalty. Thus, the results of this study not only reinforce previous findings but also provide new contributions with an approach based on actual behavioral data (behavioral clustering), which is able to empirically map music consumption patterns based on quantitative features such as skip rate, total hours streamed, and average stream duration. These findings are also in line with the results of Damayanti's research [20], which grouped popular songs on Spotify in 2024 using the K-Means Clustering method. This study proves the effectiveness of this algorithm in mapping patterns of popularity and music preferences based on audio characteristics and other digital metrics.

3.5 Model Validation Using the Silhouette Coefficient

In addition to the visualization results, the validity of the K-Means Clustering model was also reinforced through evaluation using the Silhouette Coefficient metric. This coefficient measures how well each data point is placed in its respective cluster compared to other clusters. The test results showed a silhouette score of 0.57 for

Free users and 0.64 for Premium users. These values fall into the "good" category, which means that the separation between clusters is quite clear and each cluster has a high level of internal homogeneity. These findings are consistent with the visual patterns in the PCA results, where the distribution of data between clusters appears to be separated by relatively clear boundaries, especially in the Premium group. Thus, the combination of visual results and quantitative validation metrics shows that the K-Means model used has produced optimal and consistently interpretable clustering.

Overall, the distribution of cluster results and PCA visualization show that the K-Means algorithm successfully identifies Spotify user behavior patterns effectively and interpretively. The difference in cluster structure between Free and Premium users confirms that the service model directly affects the intensity and consistency of digital music listening behavior. Premium users display more homogeneous and consistent behavioral tendencies, reflecting stable preferences and uninterrupted listening comfort. Conversely, Free users exhibit wider and more dynamic variations in behavior, influenced by feature limitations, advertising interventions, and potentially more restricted music access. These results provide empirical evidence that service experience quality is an important determinant in shaping digital music consumption patterns. Thus, this analytical model can serve as a basis for developing personalized content recommendation strategies and designing more adaptive features tailored to user characteristics in the future.

From an academic perspective, these findings enrich the study of digital music consumption behavior, particularly in the context of user experience differentiation based on subscription service models. In practical terms, the results of this study can be used as a reference for online music platform developers such as Spotify in designing user retention strategies and behavior-based recommendation systems. Segmentation formed through the K-Means approach allows for more personalized management of user experiences, for example by adjusting promotions, playlist recommendations, or interactive features according to the characteristics of each cluster. On the other hand, these results also provide opportunities for further research that integrates non-technical factors such as genre, mood, or social context into user behavior modeling, thereby producing a more comprehensive understanding of the dynamics of digital music consumption.

Although the results obtained provide a clear picture of the differences in the behavior of Free and Premium users, this study has limitations in that the data coverage only covers a period of one year and does not consider contextual variables such as geographic location or genre preferences. Therefore, further research is recommended to use a broader dataset and combine multivariate analysis approaches so that the results obtained are more representative.

4. Conclusion

Analysis using the K-Means clustering algorithm with an optimal k of three clusters shows significant differences between the behavior of Spotify Free and Premium listeners. Among Free users, the cluster proportions of 34.8%, 23.6%, and 41.6% show a tendency to listen with an average skip rate of 28.7% and a duration of 3.4 minutes, reflecting a fast and varied consumption pattern. Meanwhile, Premium users had a distribution of 29.5%, 32.8%, and 37.7%, with a lower skip rate (16.2%) and longer listening duration (3.9 minutes). *The* silhouette score of 0.57 for Free and 0.64 for Premium indicates good cluster separation and strong behavioral consistency. These results confirm that service models influence the intensity and consistency of listening behavior and can form the basis for developing personalization strategies and enhancing user experience on digital music platforms.

This study contributes to the understanding of music consumption patterns based on quantitative data and demonstrates the potential application of behavioral analysis to support decision-making in the digital music industry. Further research is recommended to add demographic variables and music preferences to produce more comprehensive user segmentation and consider the use of other clustering methods to compare grouping results in greater depth.

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