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SEGMENTATION OF SUPERBANK APPLICATION USER CHARACTERISTICS USING K-MEANS CLUSTERING

Romi Pandu Wynalda[1], Rudi Setiawan[2*]

[1,2]Department Information System, Trilogi University
South Jakarta, Indonesia

e-mail: romiwynalda14@gmail.com, rudi@trilogi.ac.id*

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Abstract

This study aims to identify the segmentation of Superbank user behavior based on application usage patterns and their relationship with onboarding channels. The research was conducted using the K-Means clustering method on user behavior data, which includes login months, transaction months, feature usage, and onboarding channels. The results of the study show that the grouping of users results in three main clusters that are aligned with the onboarding channel, namely OVO, Grab, and Superbank App. The Superbank App user cluster shows the highest level of activity, characterized by greater login frequency, higher transaction intensity, and broader feature exploration with an average feature usage score of 4.24. The feature usage variable is measured as an aggregated score reflecting the number and diversity of features utilized by users, scaled in a range of 1-5 to represent increasing levels of engagement, where higher values indicate more extensive feature adoption. Grab's user cluster demonstrates moderate usage and shows potential for improvement through a phased engagement strategy, with an average feature usage score of 2.81. Meanwhile, OVO user clusters tend to have low login frequency, more transactional usage patterns, and limited feature exploration, with an average feature usage score of 1.38. These findings suggest that onboarding channels not only serve as user acquisition pathways but also relate to post-acquisition behavior in app usage. Thus, the results of clustering can be used as the basis for developing a more targeted business strategy, especially in efforts to retain users, activate features, and increase engagement according to the characteristics of each channel.

Keywords: *K-Means clustering, User segmentation, User behavior, Engagement, Retention*

1. INTRODUCTION

In the era of rapid digital transformation, mobile applications and online platforms have become an integral part of people's daily activities [1]. These developments have encouraged an increase in the number of digital services in various sectors, including digital banking, which are competing to offer convenience, speed, and an increasingly personalized user experience. However, this growth is also accompanied by highly competitive market dynamics and increasingly complex and unpredictable user behavior [2]. Users can download the application, use it actively for a short period of time, then disappear, return to using the service at a certain period, make a transaction, or even stop completely in a relatively quick time [3]. This condition shows that the success of an application is not only determined by the number of downloads, but also by the company's ability to understand user behavior patterns on an ongoing basis.

In the context of mobile banking, the challenge lies not only in early adoption, but also in the sustainability of use. The literature shows that engagement, trust, and quality of app experience strongly determine whether users continue to use the service after the initial phase of use [4]. These findings confirm that the main problem in digital business is not only acquiring new users, but also maintaining user engagement in the long term. In this context, traditional marketing approaches that rely solely on demographic characteristics are becoming increasingly inadequate to explain the actual behavior of users. Information such as age, geographic location, and gender can provide a general overview of a consumer profile, but it does not sufficiently capture how users interact with the application over time. These limitations become even more pronounced in the privacy-first era, where global regulations such as the General Data Protection Regulation (GDPR) and App Tracking Transparency (ATT) policies restrict access to and usage of personally identifiable data for user targeting [5]. As a result, organizations are compelled to shift from identity-based segmentation toward behavior-based analysis that relies on anonymized and interaction driven data. This shift necessitates analytical methods capable of uncovering hidden patterns directly from user activity without depending on sensitive personal information. Therefore, behavioral segmentation is becoming increasingly important, as it enables the grouping of users based on actual actions recorded within the system [6]. In this context, unsupervised learning approaches particularly the K-Means algorithm offer a robust and scalable solution for identifying latent user segments, allowing organizations to derive meaningful behavioral insights while remaining compliant with data privacy constraints.

Behavioral segmentation is defined as the process of grouping users into segments based on their patterns of actions when interacting with a business or app [7]. In practice, this analysis can be carried out through observation of various behavioral variables, such as the frequency of application use, session duration, intensity of access to certain features, and purchasing or transaction decision-making patterns. Through an understanding of these variables, companies can identify the behavioral tendencies of each user group more specifically. The results of segmentation can then be used to change the communication approach from mass messages to more personalized, relevant, and in accordance with the characteristics of each segment [8]. In other words, behavioral segmentation provides a stronger foundation for companies to design retention strategies, personalize services, and develop user experiences.

Furthermore, behavioral segmentation also provides strategic benefits for business growth because it can help companies identify interaction patterns and customer purchase patterns more accurately. This information is important to support more precise market targeting, improve user retention, and drive repeat sales [9]. In the context of digital banking applications, this kind of analysis becomes very important because user loyalty is not only determined by the existence of the application, but also by the intensity of use of features, consistency of transactions, and user experience while interacting with services. Therefore, understanding user behavior is an important foundation for companies to develop a data-driven loyalty increase strategy.

To process user behavior data into meaningful information, an analysis method is needed that is able to identify hidden patterns in the data set. One of the methods that is widely used in segmentation analysis is the K-Means clustering algorithm, because it has ease of implementation and efficiency in partitioning data into groups based on similarity of characteristics [10]. Through this method, users can be automatically grouped into segments that have similar behavior patterns. However, in order to achieve optimal grouping results, the implementation of K-Means requires careful pre-processing of data, including cleaning of blank data, selecting relevant variables, and standardizing features using methods such as StandardScaler so that differences in scale between variables do not affect the accuracy of the model.

Although K-Means' behavioral segmentation and algorithms have been widely used in various digital business research and practices, there are still research gaps that need to be further studied. So far, many segmentation studies have focused on the context of digital business in general, while the application of behavioral segmentation in digital banking applications, particularly those based on users' daily activity data, still requires more in-depth exploration. In addition, segmentation research does not always link user grouping results to concrete strategic implications for increased user loyalty. In fact, in the digital banking industry, the identification of user segments will become more valuable if it does not only stop at mapping group characteristics, but also produces a decision-making basis that can be used to design retention and loyalty strategies in a more targeted manner.

Based on this background, this study was conducted to analyze the segmentation of user behavior in the Superbank application using the K-Means algorithm. The behavioral variables analyzed in this study included logins month, transactions month, feature usage (application feature usage score on a scale of 1 to 5) and onboarding source. Through these variables, this study aims to extract knowledge from raw data on user activities to identify user categories automatically and accurately. More specifically, the objectives of this study are (1) to map the behavioral segments of Superbank application users based on the similarity of their activity characteristics; (2) identify the unique characteristics of each user segment formed; and (3) analyze the implications of the segmentation results on the strategy of increasing business and loyalty of Superbank application users. Thus, the results of this research are expected to make a practical contribution to companies in increasing user satisfaction, building brand loyalty, and maintaining business sustainability in the midst of increasingly fierce digital market competition.

2. RESEARCH METHODOLOGY

2.1 Research Design

This study uses a quantitative approach with a data miningmethod to segment the behavior of Superbank application users. The technique used is unsupervised learning, specifically the K-Means clustering algorithm, which aims to group users into several segments based on the similarity of their behavioral patterns. This approach was chosen because it is able to identify hidden structures in the data without the need for class labels beforehand.

2.2 Dataset

The data used in this study is activity log data on the user onboarding channel in the Superbank application. The data used is in the form of monthly user activity with a total of 3,000 rows (1 row represents 1 user). The variables analyzed consisted of logins month, transactions month, feature usage (application feature usage score on a scale of 1 to 5) and onboarding source. UserID treated as a meta-attribute for interpretation needs is anonymous to maintain user privacy.

2.3 Pre-processing

K-Means is sensitive to scale differences between features, so all numerical variables need to be normalized so that each feature contributes more evenly when calculating distances. This stage aims to prevent variables with larger ranges from dominating the formation of cluster centroids.In this research, normalization was performed using the StandardScaler technique, which standardizes each feature by transforming it into a distribution with a mean of zero and a standard deviation of one. This approach is particularly important given the different units and value ranges of variables such as loginfrequency and transactionfrequency. Without scaling, variables with higher absolute values or wider ranges such as transaction counts could disproportionately influence the clustering process. By applying StandardScaler, both ‘Login’ and ‘Transaction’ variables are placed on a comparable scale, ensuring that the distance calculations in the K-Means algorithm reflect balanced contributions from each feature.

2.4 K-Means Clustering

The K-Means algorithm operates through an iterative process consisting of assignment and update steps, where each data point is assigned to the nearest centroid, and the cluster's centroid is recalculated based on the average of the assigned points. This process is repeated until convergence is achieved, thus minimizing the within-cluster sum of squares [11]. In this study, the number of clusters was set at K=3 based on the results of the initial evaluation using the Elbow Method, which is by observing the elbow points on the within-cluster sum of squares depreciation graph to determine the number of clusters that provide a balance between the quality of grouping and the efficiency of the model. The results of the analysis show that K=3 is the most adequate number of clusters because after this point the within-cluster sum of squares decreases to a decrease, so that the addition of clusters no longer provides a significant increase. In addition to being technically supported, the selection of three clusters is also considered from the perspective of business interpretation so that the segmentation results are concise, easy to understand, and actionable in the preparation of user loyalty strategies. Centroid initialization uses K-Means++ to reduce the risk of suboptimal starting point selection, with 10 iterations and a limit of 300 iterations to improve solution stability. The K-Means process is carried out through the following stages.

1. Specify the number of clusters (k)
2. Randomized centroid initialization
3. Calculating distances between data using Euclidean Distance
4. Groups data to nearby centroids
5. Update centroids based on average cluster members
6. Repeat the process until it converges

This method is used in customer segmentation because of its ability to segment data efficiently [12].

2.5 Process Tools and Flows

The whole process is done in Orange Data Mining using a series of widgets: CSV File Import -> Select Columns -> K-Means -> visualization (Distributions, Scatter Plot, Box Plot) as show in Figure 1. The main output is the cluster labels per user and a summary of the onboarding source distribution on each cluster.

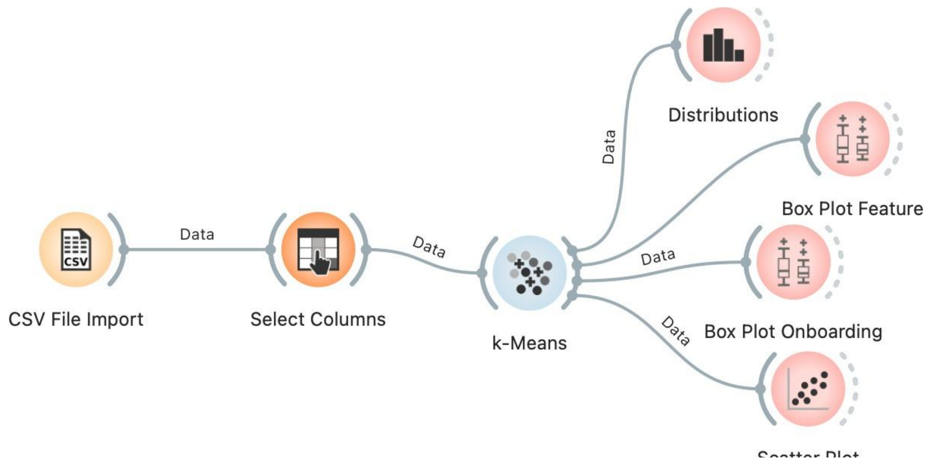

Figure 1. The clustering process flow in Orange Data Mining.
[Source: Authors, 2026]

3. RESULT AND DISCUSSION

3.1. Distribution of Onboarding Sources Across Clusters

Figure 2 presents the distribution of onboarding sources (Grab, OVO, and Superbank App) across the three identified clusters (C1, C2, and C3). The results show a clear differentiation in the dominance of onboarding channels across clusters. Cluster C1 is dominated by OVO, with a significantly higher frequency compared to other sources. This indicates that users in this cluster primarily enter the platform through the OVO ecosystem. In contrast, the contribution from Grab is minimal, and the Superbank App shows a moderate representation. Cluster C2 shows the strong dominance of Superbank as the primary onboarding channel, while OVO makes a very small contribution. The Superbank App appears in this cluster but only at a relatively low frequency, indicating a partial diversification of onboarding channels. Cluster C3 shows the most distinct pattern, with onboarding driven almost exclusively by Grab. The contribution of other sources in this cluster is very small, indicating highly concentrated onboarding behavior.These findings suggest that sign-up sources play a significant role in differentiating user segments, with each group reflecting a unique entry path into the platform ecosystem.

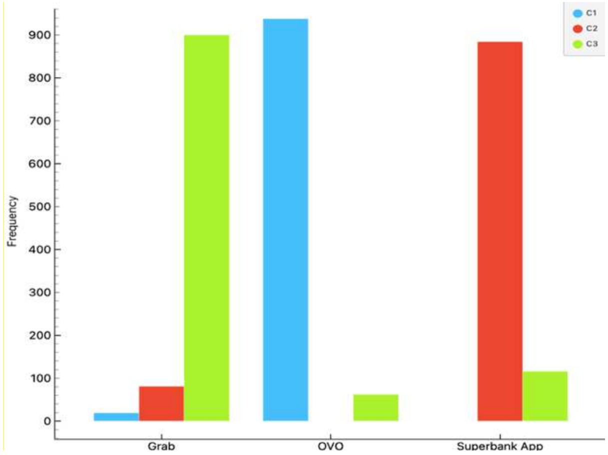

Figure 2. Distribution of onboarding sources in each cluster.
[Source: Researcher analysis results, 2026]

3.2. Distribution Consistency of Onboarding Sources

Figure 3 illustrates the distribution of onboarding sources within each cluster using box plot visualization. This figure provides insights into the variability and consistency of onboarding patterns across clusters.Cluster C1 shows a highly concentrated distribution near the upper bound (close to 100) for OVO, indicating strong dominance and low variability. This suggests that users in C1 are highly homogeneous in terms of onboarding behavior, with OVO serving as the primary and consistent entry point. Cluster C2, while still dominated by Superbank, exhibits slightly higher variability compared to C1. The presence of Superbank App introduces minor dispersion, indicating that this cluster is less homogeneous and may represent users transitioning across multiple onboarding channels. Cluster C3 displays the highest level of consistency, with values tightly concentrated near 100 for Grab. This confirms that C3 is the most homogeneous cluster, characterized by a nearly exclusive reliance on Grab as the onboarding source.

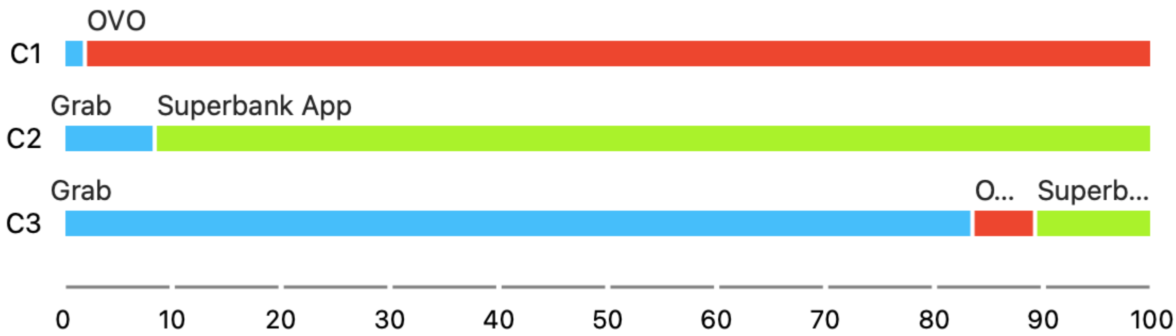

Figure 3. Box plots onboarding distribution per cluster.
[Source: Researcher analysis results, 2026]

3.3. Integrated Analysis of Onboarding Patterns

The combined interpretation of Figures 2 and 3 provides a comprehensive understanding of onboarding behavior. While Figure 2 highlights absolute frequency differences, Figure 3 complements this by revealing the degree of variability within each cluster.Clusters with strong dominance in Figure 3 correspond to tightly concentrated distributions in Figure 2, indicating low variance and high homogeneity. Specifically, C3 emerges as the most stable and clearly defined cluster, followed by C1. In contrast, C2 shows relatively higher variability, suggesting a more heterogeneous user composition.This alignment between frequency distribution and dispersion analysis confirms the robustness of the clustering results, as each cluster demonstrates internally consistent behavioral patterns.

3.4 Login intensity and number of transactions

The scatter plot (Figure 4) shows a clear relationship between login intensity and the number of transactions in each cluster, while also showing a pattern of segmentation of user behavior. Cluster C1 (blue) is displayed with a moderate login frequency but a relatively high number of transactions. This indicates that users in this cluster tend to be less active in accessing the application, but are accompanied by high transaction activity, so they can be attributed to users with strong transaction intentions.In contrast, Cluster C2 (red) shows a different pattern, where most of the points are in a higher transaction range with a fairly high login frequency. This pattern shows that users in this cluster have a deeper engagement with the platform, not only logging in frequently but also actively making transactions. Thus, this cluster can be categorized as users with high-value users who contribute significantly to business activities.

Meanwhile, Cluster C3 (green) tends to be in areas with lower login frequency and transaction numbers than the other two clusters. This shows that users in this cluster have a relatively low level of engagement, both in terms of access and transactions, so they can be categorized as passive users or low-engagement users. This scatter plot reveals a positive correlation between login frequency and transaction count, where an increase in login activity tends to be followed by an increase in the number of transactions, especially in Cluster C3. In addition, the fairly clear separation of clusters shows that the clustering model successfully identifies segmentation of user behavior based on their activity and engagement levels, which can be leveraged for service personalization strategies and user retention optimization.

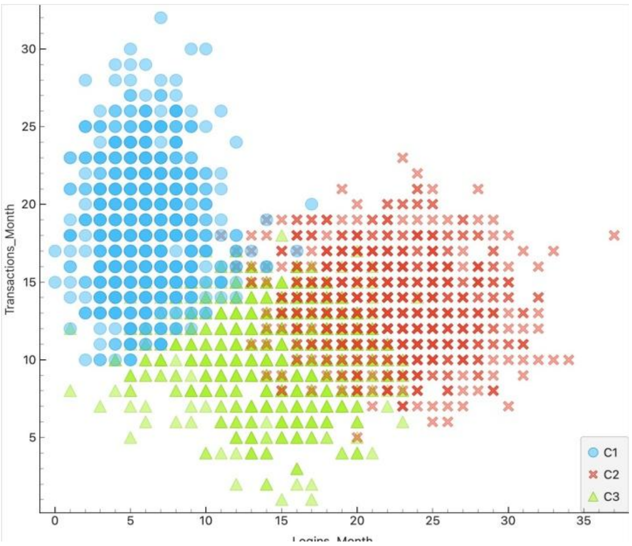

Figure 4. Scatter plots login vs transactions with cluster labels.
[Source: Researcher analysis results, 2026]

3.5 Feature usage per cluster

The box plot (Figure 5) in the FeatureUsage variable shows that there is a clear difference in the distribution of feature utilization rates between clusters. The C2 cluster had the highest average, which was 4.24 ± 0.7, followed by the C3 cluster of 2.81 ± 0.7, while the C1 cluster showed the lowest average, which was 1.38 ± 0.6. These findings indicate that each cluster has different characteristic feature usage behaviors. In particular, users in the C2 cluster tend to have a higher level of feature exploration than the other two clusters, while users in the C1 cluster exhibit relatively limited feature usage. The position of the C3 cluster in between the two indicates the existence of a group of users with a moderate level of feature exploration. This pattern reinforces the suspicion that onboarding channels are related to the depth of feature usage. In this context, users who come directly from the Superbank application seem to be more active in exploring the various features available, while users who come from OVO tend to use the service for more specific needs, especially in certain transaction use cases.

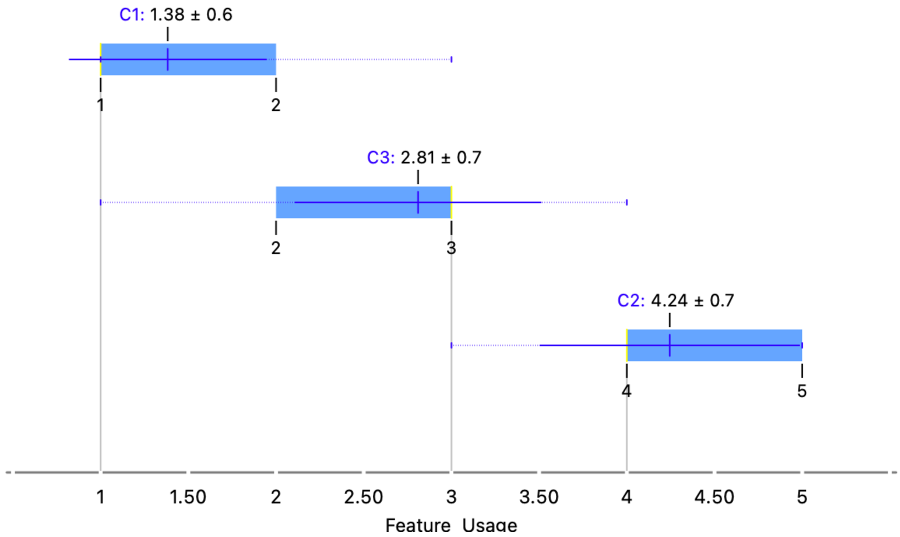

Figure 5. The box plots the feature usage score per cluster.
[Source: Researcher analysis results, 2026]

3.6. Implications for User Segmentation and Strategy

The cluster pattern formed is not only relevant for the sake of operational segmentation, but also shows theoretical implications for the formation of loyalty in digital banking. The literature confirms that digital loyalty develops through continuous use, service satisfaction, perceived value, and habituation of use, rather than solely from early adoption decisions [13].

The C1 cluster shows users who are relatively more embedded in the OVO ecosystem. The high level of familiarity with digital financial services indicates a tendency for more stable and repetitive use. In the perspective of continuance use and habit formation, this pattern suggests that services are starting to become part of the user's routine [14]. The literature also shows that satisfaction, trust, and perception of service quality contribute to long-term usage and loyalty [15]. Thus, C1 can be positioned as a segment with more mature loyalty potential and worthy of being targeted for up-selling and value-added service development.

The C2 cluster represents users closely associated with the Superbank ecosystem that show a transitional segment with a more diverse orientation. This character indicates that users are not yet fully consolidated into a single ecosystem, but have shown cross-channel engagement. Theoretically, segments like this can be read as the stage between continuance intention and habitual use [16], [17]. Therefore, C2 is a strategic segment for personalization-based interventions, cross-platform integration, and cross-selling. If the perception of benefits and service satisfaction can be strengthened, this segment has the potential to move towards more stable loyalty.

The C3 cluster represents users who are closely associated with the Grab ecosystem. The consistency of its behavioural orientation shows that Grab functions effectively as a utility-based acquisition channel. This pattern is in line with the literature that places convenience, efficiency, and quality of core experiences as the basis for sustainable use in the early stages of digital loyalty [18]. Therefore, strategies in this segment should emphasize simplifying flows, strengthening practical features, and stability of service quality so that functional satisfaction develops into stronger loyalty.

These findings suggest that differences between clusters not only reflect variations in user behavior, but also represent different levels of digital loyalty maturity. Grab appears to be more effective as a utility-oriented user acquisition channel, while OVO is closer to segments with higher financial engagement readiness. Meanwhile, Superbank is opening up space for retention strategies through experience strengthening, ecosystem integration, and increased service relevance. Thus, behavior-based segmentation through K-Means is not only practically beneficial, but can also be used to map loyalty dynamics in the context of digital banking.

3.7 Business Implications

The results of the clustering show that business strategies should not be applied uniformly across all channels, but need to be adjusted to the position of each cluster in the activation, engagement, and retention stages. From a managerial perspective, these findings confirm that differences in user behavior between channels can be translated into different interventions. The literature shows that in digital services, the initial phase of use greatly determines the sustainability of the relationship with the user [19]. Simple yet relevant onboarding interventions, such as asking users to select a usage destination or contextually displaying a guide to core features, have been shown to increase activity and frequency of visits [20]. In addition, systematic studies of digital habit formation also show that prompts and cues, goal setting, feedback, and personalization are important mechanisms for building usage routines [21]. Thus, cluster-based segmentation provides a solid foundation for designing more precise strategies according to the level of readiness and user engagement on each channel.

In the OVO cluster (C1), the most relevant business implication is to encourage the formation of basic usage habits first. The focus of the strategy on this cluster is not directly expanding usage to many features, but rather increasing the frequency of logins, understanding the benefits of core features, and simple repetition of behavior. Therefore, approaches such as re-onboarding, brief post-transaction education, contextual reminders after a successful payment, or notifications that appear at moments of repeated use are important. This approach is in line with the findings that encouragement at the onboarding stage can increase user activity and visits [22], while habit formation tends to be stronger when behaviors are triggered by a stable context, consistent cues, and positive reinforcement. This means that for C1, companies need to design experiences that help users associate the app with everyday situations, so that the app is not only used occasionally, but also fits into more automated usage patterns.

In the Grab (C3) cluster, business strategy should be directed at gradually increasing engagement through the expansion of use cases that are relevant to users' daily needs. Because this cluster is in a transition position, an overly aggressive strategy to offer all the features at once risks lowering user focus. A more appropriate approach is to provide feature recommendations in stages based on the context of transactions and routine needs, such as features that are closest to the user's daily behavior. The literature shows that technology-based personalization can increase facilitating conditions, hedonic motivation, perception of security/confidentiality, and intention to use mobile banking [23]. In addition, continuance intention in mobile services is also significantly influenced by perceived usefulness, self-efficacy, satisfaction, and adaptation, with trust strengthening the relationship between user adaptation and intention to continue use [24]. Therefore, for C3, the most rational strategy is to present next-best-feature recommendations, light education that increases the sense of being able to use new features, and messages that emphasize the practical benefits of engaging growing progressively, not instantly.

Meanwhile, in the Superbank App (C2) cluster, the business implications focus on retaining and maximizing the value of users who are relatively active. At this stage, the strategy needed is no longer basic activation, but rather strengthening loyalty through experiences that are more personalized, relevant, and valuable. Banking literature shows that customer loyalty is consistently influenced by satisfaction, trust, service quality, perceived value, perceived usefulness, and user experience [25]. Other findings in the financial services industry also show that in loyalty programs, social and exploratory benefits can be stronger drivers of loyalty than purely monetary benefits [26]. Therefore, in C2, loyalty programs are not enough in the form of cashback or transactional incentives, but need to be enriched with offer personalization, recognition of user loyalty, relevant financial insights, product recommendations that suit profiles, and strengthening the value proposition that makes users feel that the application is the most relevant for their financial needs. This strategy will help keep users active while increasing the likelihood of cross-selling and the depth of long-term relationships.

The business implications of this clustering result confirm that each channel requires different strategic priorities: C1 is oriented towards activation and habit building, C3 is towards incremental increase in engagement, and C2 is towards retention and loyalty. In other words, clustering results are not only useful for describing user behavior, but can also be the basis for allocating marketing resources, designing user experiences, and developing more efficient features. In the context of digital business management, a differentiated approach like this has the potential to result in intervention effectiveness than the same general strategy for all users.

4. CONCLUSION

This study concludes that the application of the K-Means clustering method to Superbank user behavior data is able to produce meaningful segmentation and is in harmony with the user onboarding channel. The three clusters formed showed a noticeable difference in behavior patterns, especially in the frequency of logins, transaction intensity, and depth of feature usage. The user clusters originating from Superbank App tend to show the highest level of activitybased on feature usage. Users of Grab channels are at a more moderate level of usage, with behavioral characteristics that show potential to continue to develop. Meanwhile, users of the OVO channel show a more limited usage pattern, mainly characterized by low login frequency and in-depth use of features.

The findings show that the onboarding channel not only serves as a user acquisition path, but also relates to the quality of user engagement after entering the application ecosystem. Thus, the results of this clustering confirm that the behavior of Superbank users is heterogeneous and cannot be treated uniformly. Each user group has different characteristics and management needs, so the business approach applied needs to be tailored to the profile of each cluster.

Practically, the results of this research can be used as a basis for developing a strategy for retention, feature activation, and engagement development that is more targeted at each channel. Users with high activity levels can be focused on loyalty strategies and strengthening value propositions, users with moderate activity levels can be encouraged through gradual engagement increases, while users with low activity need a basic activation strategy that emphasizes habit-building and introduction to core features. Thus, this behavior-based segmentation not only provides an academic overview of the variation in user behavior, but also has strategic value for companies in increasing the effectiveness of user management in each onboarding channel.

This study has limitations because it uses user behavior data that is still monthly aggregation, so it is not fully able to capture the dynamics of behavior change in more detail over time. In addition, the variables used are still limited to monthly logins, monthly transactions, feature usage, and source onboarding, so the segmentation results are more representative of general patterns of user behavior. Therefore, further research is recommended using data with higher frequencies and adding attributes such as account age and retention metrics, such as daily active user and monthly active user or churn, so that segmentation analysis, behavior change, and user loyalty formation can be explained in more depth.

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