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RESEARCH ARTICLE

Identification of Evaluation Results in E-Banking Services Transaction for Product Recommendation using the BIRCH and Davies Bouldin Index Method

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Abstract: E-banking transaction services in the banking world include many products offered to customers. However, the existence of regulatory factors may limit the extent to which banks can promote e-banking services, especially in cases where promotions involve incentives or special offers. Besides, this research aims to help recommend product promos from these services by using data analysis. Recommendations for this product promo can be known from the evaluation process of data collected from e-banking transaction services for purchases and payments. The research method that is used for this research is the clustering method. The clustering method for providing significant and influential results compared to other methods suitable for this research is BIRCH, which is assisted by the Davies Bouldin index method to determine the list of product groups with the lowest value. The results of this research depicted that data can be grouped based on which services have low use levels. The services in question are Deposits, Credit Cards on Mobile Services, OVB, and Inter-Bank Transfers on Mobile Services. Therefore, this service can be used as a reference to increase product promotion by the bank. These services can be used as a reference by the bank to improve promotions so that all services can be used and utilized well by customers, thereby increasing the value of the bank's services.

Keywords: BIRCH, K-Means, Minibatch K-Means, Clustering, E-Banking Services, Product Recommendation

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1 Introduction

E-banking transaction services include fund transfers, bill payments, balance checks, and other banking activities that can be accessed electronically via the Internet or banking applications. E-banking transaction services are in excellent customer demand because they provide easy banking access, time efficiency, and convenience [1]. Users can carry out various transactions anytime and anywhere without coming directly to the bank. Apart from that, its advanced security features also make it increasingly popular with users.

The bank promotes e-banking services through various marketing channels, including advertisements on social media, television, radio, and newspapers. They can also organize unique promotional campaigns to attract the attention of potential customers. Offering special discounts, incentives, or bonuses for using e-banking services is also often used as a promotional strategy. In addition, the bank also focuses on consumer education, explaining the benefits and convenience of e-banking services through marketing materials and online guides. Several obstacles to promotional strategies at banks involve security concerns, mainly due to increased cybercrime cases.

Furthermore, obstacles may arise from challenges in effectively communicating the advantages of e-banking services to consumers and a need for more awareness regarding online security. Regulatory constraints can also restrict the extent banks can promote e-banking services, particularly when incentives or special offers are involved. Lastly, unequal access to technology or a deficiency in digital literacy within specific segments of society can pose additional barriers.

Moreover, customers' responses to e-banking services tend to differ. Many customers embrace this service favourably due to its convenience and accessibility, regularly engaging in online transactions, balance checks, and utilizing various e-banking features. Nonetheless, some customers may still require reassurance regarding the security of online transactions and may lean towards traditional methods [2]. Customer behavior in e-banking is influenced by age and digital literacy levels. Banks actively enhance security measures, offer educational initiatives to alter perceptions, and promote the adoption of e-banking services.

Recommendations for e-banking service products from the results of data analysis have several benefits. First, it can improve user experience by providing solutions that suit their needs and transactional behavior [3]. Second, it helps increase the penetration of e-banking services by providing relevant advice to users, encouraging wider adoption of the service. Third, improve customer retention by providing added value through accurate and useful recommendations. Data analysis allows banks to understand customer behavior patterns and provide more personalized and tailored recommendations.

Several researchers proposed clustering as a suitable method for the banking transaction domain [4–8]. The clustering method is a data analysis method that groups objects or data into similar groups based on specific characteristics or attributes. Some popular clustering methods include K-Means, Minibatch K-Means, Hierarchical Clustering, BIRCH, and DBSCAN [6]. The main goal of this method is to create groups that are homogeneous within them and heterogeneous between them. Clustering is used in various fields, such as data mining, pattern analysis, and market segmentation.

In e-banking services transactions, market segmentation employs clustering to categorize customers according to their transactional behavior, banking requirements, or risk profiles. This aids banks in delivering more personalized services and devising more efficient marketing strategies. Clustering is also utilized to pinpoint suspicious transaction patterns or identify groups of accounts potentially engaged in illicit activities, thereby enhancing security and fraud detection in banking operations. Additionally, clustering assists in grouping financial instruments or investment portfolios with similar risks, aiding banks in risk management and investment decision-making. Besides, financial institutions can optimize operations, enhance customer service, and better manage risks by applying clustering techniques to banking data.

2 Research Method

At this stage, a series of procedures or systematic approaches are used by researchers to plan, implement, and analyze data. Research methods help ensure that the research process is carried out well so that the results are reliable and can be interpreted correctly. The research methods for this research include the steps researchers take to design studies, collect data, and model data to obtain expected results. Figure 1 shows the research steps taken to get product promotion recommendations based on the results of evaluating e-banking transaction services using the clustering method. A detailed explanation of each step can be seen in the following subchapter.

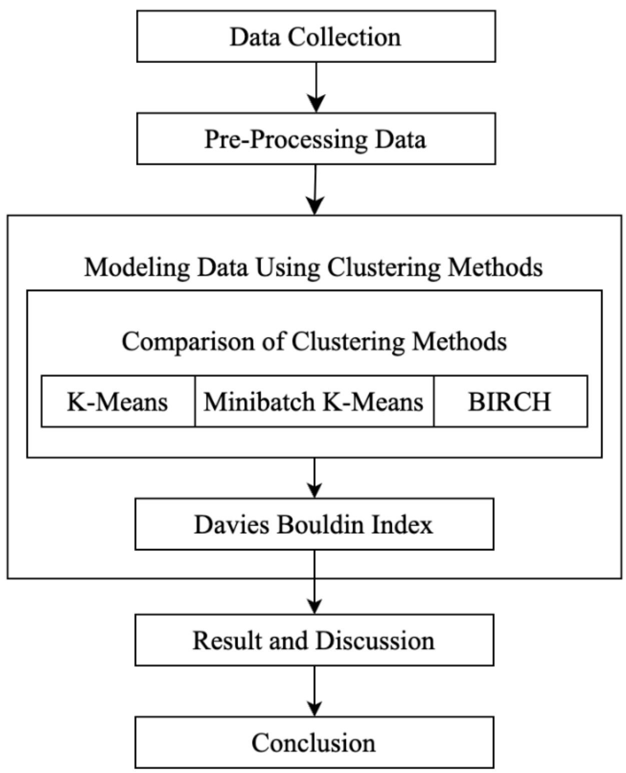

Figure 1: The architecture of the e-banking service product promo recommendation process using the clustering method.

2.1 Data Collection

Research methods include ways of collecting data appropriate to the research objectives. This may involve using interviews, questionnaires, observations, experiments, or various methods. In this research, data collection was carried out with a focus on in-depth analysis of one case. Apart from that, there were direct observations and interviews with banking parties from Bank PT. XYZ is combined with literature studies to obtain the expected research results. Figure 2 is an example of e-banking transaction data from PT. XYZ from 2016-2023 (*TotalJumlah* -> Sum; *KodeRegional* -> Regional Code; *Nominal* -> Nominal). This data is used as a reference for evaluating e-banking transaction services so that the bank can obtain later information for product promotion recommendations.

TglTransaksi	ServiceName	NamaPemilikRekening	NamaInstansi	TotalJumlah	KodeRegional	Nominal
2016-01-01 00:00:00.0000000	INTERNET Bill Payment	RIZKI PRXTXMX	Kartu Kredit Mega	681716.55	804.0	681716.55
2016-01-01 00:00:00.0000000	INTERNET Bill Payment	RXTIH CHXNDRX DXWI	Kartu Kredit Mega	83350.00	807.0	83350.00
2016-01-01 00:03:21.0000000	INTERNET Bill Payment	RXTIH CHXNDRX DXWI	Kartu Kredit Mega	5125000.00	807.0	5125000.00
2016-01-01 00:39:11.0000000	INTERNET Purchase	RXTIH CHXNDRX DXWI	Listrik Prabayar (PLN)	203500.00	807.0	200000.00
2016-01-01 07:49:50.0000000	INTERNET Bill Payment	XGXS BXSRI L	Kartu Kredit Mega	1668750.00	811.0	1668750.00

Figure 2: Sample of e-banking transaction data.

2.2 Pre-Processing Data

Data pre-processing is a series of steps or techniques performed on data before the data can be used for analysis or modelling [1]. Data pre-processing ensures that the data used in research or modelling is good quality, clean, and ready to use. Following are some general steps in data pre-processing:

1. Data Cleaning
   This process is carried out to resolve and handle missing or incomplete data, detect and handle outliers or abnormal values, and identify and handle duplicates in the data [9]. Additionally, it reduces the number of variables or features in the data if necessary. This technique also holds missing values by filling in or deleting empty data.
2. Data Transformation
   Data transformation is carried out to normalize or standardize the data to ensure that all variables have a similar scale and carry out logarithmic or other adaptations to change the data distribution if necessary [9]. Additionally, the format or data type is changed if required.

3. Encoding Categorical Variable
   Here, we will convert categorical variables into a form that can be used in analysis or modelling, such as one-hot encoding.

The results of data preprocessing will then be used in the data modelling stage using the clustering method to obtain product recommendations from e-banking transaction services.

2.3 Data Modeling using Clustering Methods

Selection of the appropriate clustering method depends on the nature and structure of the data, as well as the desired analysis objectives [7,10–12]. Three clustering methods are popular for banking transactions: K-Means, Minibatch K-Means, and BIRCH. The methods can group the number of large datasets. However, comparing the methods is used to choose the best method to provide the best cluster result from the modelling phase. Therefore, the clustering results can be evaluated using the Davies-Bouldin score. Data modelling with clustering involves grouping data into similar groups based on specific characteristics or patterns [13]. The main goal of clustering is to group data so that data in groups has high similarities while different groups have significant differences. There are several commonly used clustering methods.

1. K-Means
   K-Means is a popular clustering method in data analysis. This method groups data into k groups (clusters) based on similar attributes. The result is grouping the data into k groups, where each has its center [1, 2, 10]. K-Means is iterative and can efficiently solve clustering problems with large amounts of data. K-Means can be suitable for the analysis of banking e-banking services. K-Means can help banks group customers based on e-banking service usage patterns. This allows banks to understand customer needs and preferences to provide more tailored services. Banks can analyze customer transaction patterns using K-Means and identify groups with similar transactional behaviour. This can help in developing more effective service and promotion strategies. In addition, K-Means can be used to compile a product portfolio that better suits the needs of each customer group. Banks can customize e-banking products and service offerings based on the characteristics of each segment. By understanding different customer groups, banks can improve the user experience by presenting a more tailored interface and providing relevant service recommendations. K-Means can also analyze suspicious transaction patterns or groups requiring more security attention. Although K-Means has its advantages, it should be noted that the results can be affected by initialization and can produce rounded clusters, which may only sometimes reflect the actual structure of the data. Therefore, interpretation of K-Means results needs to be done carefully.
2. Minibatch K-Means
   Minibatch K-Means is a variation of the K-Means algorithm designed to overcome some of the computational challenges associated with processing large amounts of data [1, 10]. In the conventional K-Means algorithm, the entire dataset is used to update the cluster centers at each iteration, which can be computationally expensive if the dataset is huge. In Minibatch K-Means, processing is performed on a small portion or "minibatch" of the dataset at each iteration. Minibatch K-Means provides

a trade-off between computational efficiency and accuracy. Although the results may differ slightly from conventional K-Means, this approach allows faster processing, especially on large datasets. Minibatch K-Means is generally used in the context of big data or when computing resources are limited. The main difference between K-Means and Minibatch K-Means is how the two methods process data. K-Means uses the entire dataset to calculate and update cluster centers at each iteration. Meanwhile, Minibatch K-Means only randomly uses a small amount of data (minibatch) of the whole dataset at each iteration. In addition, K-Means can update cluster centers based on the entire dataset at each iteration. Meanwhile, Minibatch K-Means can update cluster centers based on the minibatch selected at each iteration. K-Means may also be more computationally expensive, especially on large datasets, because it involves processing the entire dataset at each iteration. Meanwhile, Minibatch K-Means is more computationally efficient because it only processes a small amount of data at each iteration. This makes it more suitable for handling big data or when computing resources are limited.
Another thing is that K-Means is more likely to provide accurate results because it uses the entire dataset in each iteration. Minibatch K-Means provides results that may differ slightly from K-Means because it only uses a small sample of data. However, this is often accepted as a trade-off for computational efficiency. The choice between K-Means and Minibatch K-Means depends on the size of the dataset, the availability of computing resources, and the desired level of accuracy. Minibatch K-Means is often used when handling big data, or resource limitations are important factors. In the context of e-banking, Minibatch K-Means can provide several advantages regarding computational efficiency and data analysis. Minibatch K-Means can help banks group e-banking customers into segments based on transactional behaviour or service usage. This allows banks to customize marketing strategies and services according to the preferences and needs of each part. In managing large volumes of e-banking transactions, Minibatch K-Means can provide computational efficiency by processing a small number of transactions at each iteration. This can help in improving system performance and responsiveness. Minibatch K-Means can be used to analyze suspicious or unusual transaction patterns. Banks can efficiently detect suspicious activity without processing the entire dataset by batching several transactions at each iteration. By understanding small segments' e-banking service usage patterns at each iteration, banks can improve the personalization of services and user interfaces for a better user experience. Applying Minibatch K-Means in e-banking can help banks overcome the challenges of handling big data while providing relevant and efficient analysis. However, as with any analytical method, interpretation of results and data security considerations must be carefully considered.

3. BIRCH
The balanced iterative reducing and clustering using hierarchies (BIRCH) method is a clustering algorithm designed to handle large amounts of data and build hierarchical structures efficiently [14–16]. Here are some of the main characteristics of the BIRCH method:

- Use of clustering feature (CF) trees: BIRCH uses a tree structure called a clustering feature tree (CF Tree) to represent data and group it based on specific attributes.

- Iterative and incremental: This algorithm works iteratively and incrementally, which means it processes data gradually and can adapt to adding new data without re-processing the entire dataset.
- Use of cluster feature (CF): Each node in the CF tree stores statistical information, such as the number of objects, squares, and the center of mass of the objects represented by that node. This allows BIRCH to make clustering decisions quickly.
- Dynamic cluster selection: BIRCH can dynamically determine the optimal number of clusters based on the CF tree structure, avoiding determining the number of groups in advance.
- Scalability and Efficiency: Designed to handle large datasets, BIRCH achieves scalability by grouping data incrementally and efficiently using a tree structure.

The BIRCH method is generally suitable for applications where data grouping based on a hierarchical structure and extensive data handling are required, such as log analysis, data streaming processing, and clustering on geospatial data. In e-banking, the BIRCH method can be applied for various purposes related to data analysis and customer grouping. BIRCH can group e-banking customers based on service usage patterns, number of transactions, or risk profile. This helps banks understand customer preferences and needs to provide more tailored services. BIRCH can assist in efficient and large-scale processing by grouping e-banking transactions iteratively and incrementally. This can be applied to improve system performance and responsiveness to customer transactions. BIRCH can be used to detect suspicious transaction patterns or unusual groups of data, which could be potential indicators of fraudulent activity or questionable security. By understanding the cluster hierarchy, banks can provide more personalized services tailored to the needs of each customer group. This may include product recommendations, special offers, or customized user interfaces. BIRCH can help banks analyze hierarchical structures in e-banking data, such as relationships between accounts and subaccounts or incremental transactions over time. Applying BIRCH in e-banking can benefit from efficiently managing and analyzing big data, enabling banks to make smarter decisions and provide more relevant customer services. However, as with all analytical methods, interpretation of results and data security need to be a primary concern.

4. Davies Bouldin

The Davies-Bouldin index (DBI) is an internal evaluation metric to assess a dataset's clustering quality. It measures how well-separated and compact the clusters are. A lower DBI indicates more homogeneous and well-separated clusters [17–20]. A better (lower) DBI is achieved when clusters are more homogeneous (smaller distances within clusters) and well-separated from each other (more considerable distances between clusters). The DBI is a measure of how well-separated and compact the clusters are. Here's a general outline of the steps to calculate the DBI:

- Form clusters using a clustering algorithm (BIRCH) on your e-banking transaction data. Calculate the centroid (average position) for each cluster based on the data points' features.
- Calculate the distances between data points within each cluster and between clusters. Standard distance metrics include Euclidean distance, Manhattan distance, or other appropriate measures based on the data characteristics.
- Calculate the normalized Davies-Bouldin value and the DBI as the average of each normalized DBI value for all clusters.

A good clustering will have a DBI close to zero. The Davies-Bouldin index is one of several internal evaluation metrics used to assess clustering quality. While useful, it's essential to consider other metrics and contextual understanding related to the data and analysis goals for a comprehensive evaluation. A lower DBI indicates better cluster separation and compactness. Choosing an appropriate clustering algorithm and evaluating the results in the context of your e-banking transaction data and specific goals is essential. Additionally, we need to experiment with different clustering methods and parameter settings to optimize the DBI for your dataset.

The clustering method in data modelling shows that the BIRCH method has higher accuracy results than other methods. This can be seen in Figure 3.

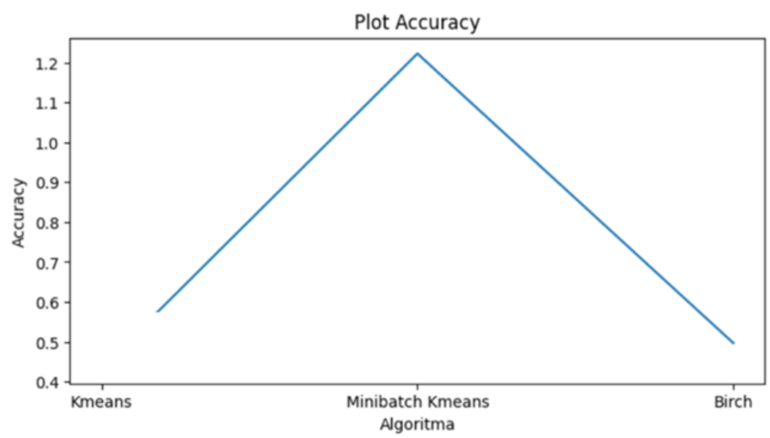

Figure 3: Comparison results of data modelling accuracy with the clustering method.

The BIRCH method provides better data cluster results than other methods. This accuracy value can be seen from the error value; the fewer errors given, the higher the accuracy value. Therefore, the BIRCH method will be applied to produce product promo recommendations based on evaluating the e-banking service data. The use of the Davies Bouldin index can be evaluated in the BRICH method after this method is implemented. A more detailed explanation is in the next chapter.

3 Result

The BIRCH method is chosen for cluster processing purchase and payment e-banking transaction service data. The data that has been collected has, of course, gone through data pre-processing. The robust scaler technique is used to normalize and overcome outliers, fit training data, and test data transformation to avoid data leakage. Figure 4 shows the results of the data transformation.

The data that has passed pre-processing is then processed using the elbow method, which is used in data modelling using the BIRCH method to help determine the optimal number of groups or clusters for a data set. The elbow method aims to identify where increasing the number of clusters does not significantly improve clustering quality. This

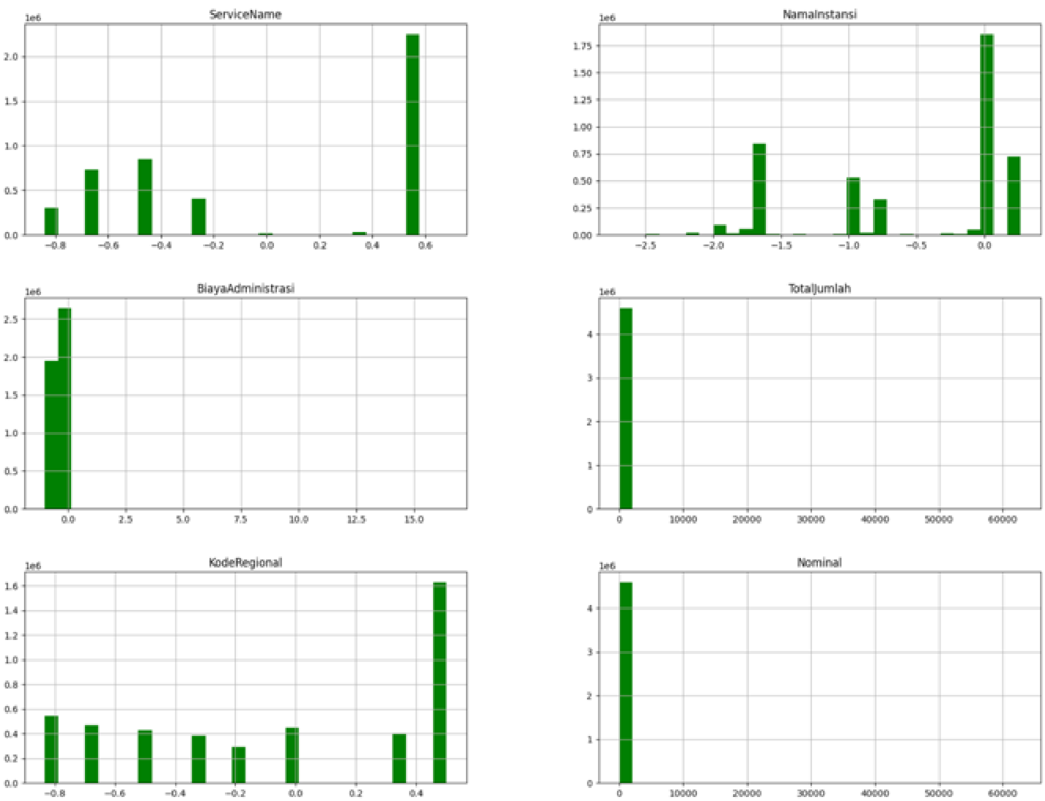

Figure 4: Normalization results using robust scaler.

method can also evaluate the quality of clustering with various numbers of clusters with optimal values in a hierarchical structure. Figure 5 is a clustering result from the elbow method with optimal cluster values.

Figure 5 shows the results of grouping data, namely k=3. BIRCH forms a hierarchical structure, so the optimal number of clusters may be more subjective. Two different group results were obtained from the cluster results. This grouping was then used for further analysis using the Davies-Bouldin method. This method scores the groups of e-banking transaction services that are most widely used and customers most commonly use. Figure 6 shows purchase and payment transaction data details for e-banking services (*TotalJumlah* -> Sum; *KodeRegional* -> Regional Code; *Nominal* -> Nominal). Meanwhile, Figure 7 provides an overview in the form of a graphic of what services the evaluation results need to be reviewed or focused on for product promotion by the Bank to its customers.

Figure 6 and Figure 7 depict that the services that need to be focused on to increase promotion are deposits, OVB, and ATB transfers on mobile services. Recommendations for e-banking service products resulting from the data processing provide several benefits. This can improve user experience by providing solutions that suit their needs and transactional patterns. It can then help increase the adoption of e-banking services by pro-

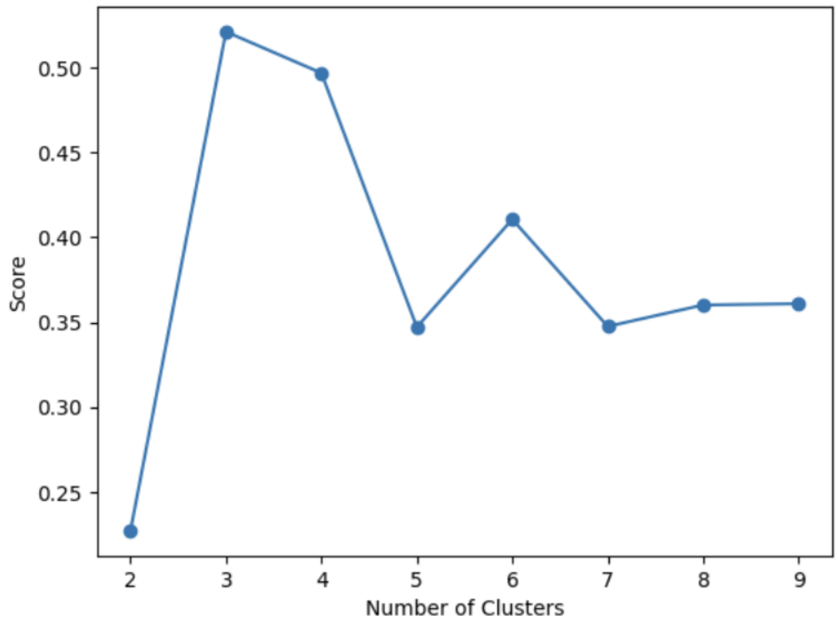

Figure 5: Cluster elbow results with optimal values.

viding relevant advice and encouraging users to adopt the service more widely. It can also improve customer retention by providing value through accurate and useful recommendations. Therefore, it allows banks to understand customer behaviour patterns and present more personalized recommendations tailored to their needs.

4 Discussion

Transaction evaluation is a process in which banks assess and analyze financial transactions carried out by customers. The results of this transaction evaluation can be used as a benchmark or basis for determining product or service recommendations that suit customer needs and transactional behaviour. The results of these transaction evaluations can form the basis for providing more personalized and relevant product recommendations for customers. Creating a better banking experience and meeting customers' needs is important.

The result of this research is that the BIRCH method and the Dalvin Bouldin score help assess how often customers make transactions and what types are usually carried out. It offers the ability to understand customer preferences and requirements, analyze the overall volume of transactions and the associated financial value, and assess customer financial capacity. Furthermore, by scrutinizing transactional activities, banks can discern customer spending patterns, identify spending preferences, and customize product recommendations. Additionally, this analysis can highlight additional services or product features that customers may require based on their transactional behaviour, such as digital banking, insurance, or investment services.

	ServiceName	NamaInstansi	TotalJumlah	KodeRegional	Nominal
0	INTERNET Bill Payment	Kartu Kredit Mega	681716.55	804.0	681716.55
1	INTERNET Bill Payment	Kartu Kredit Mega	83350.00	807.0	83350.00
2	INTERNET Bill Payment	Kartu Kredit Mega	5125000.00	807.0	5125000.00
3	INTERNET Purchase	Listrik Prabayar (PLN)	203500.00	807.0	200000.00
4	INTERNET Bill Payment	Kartu Kredit Mega	1668750.00	811.0	1668750.00
...	...	...	...	...	...
4595275	MOBILE Transfer Antar Bank	Transfer ATB	816500.00	804.0	810000.00
4595276	MOBILE Transfer Antar Bank	Transfer ATB	1311503.00	804.0	1305003.00
4595277	MOBILE Transfer Antar Bank	Transfer ATB	8006500.00	804.0	8000000.00
4595278	MOBILE Transfer Antar Bank	Transfer ATB	671500.00	804.0	665000.00
4595279	MOBILE Transfer Antar Bank	Transfer ATB	25006500.00	804.0	25000000.00

Figure 6: Detailed evaluation results of e-banking transaction services.

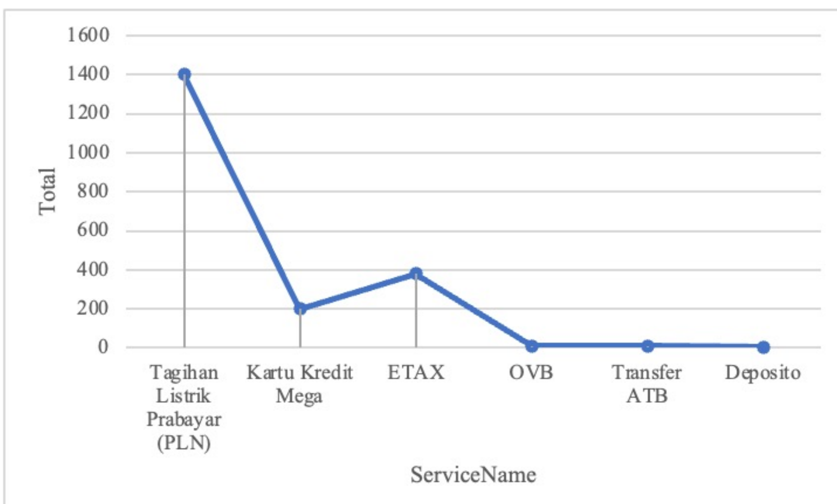

Figure 7: Graph of evaluation results of e-banking transaction services.

The BIRCH technique efficiently organizes data hierarchically. Simultaneously, the Davies-Bouldin index (DBI) assesses internal validity to gauge the effectiveness of a clustering method, with lower DBI values indicating better clustering. According to the evaluation findings, the bank is advised to intensify promotions and emphasize key services such as deposits, OVB, and ATB transfers via mobile services. Recommendations drawn from the analysis of e-banking service data present several benefits, including improving user satisfaction through providing customized solutions that align with their needs and transactional behaviours.

As a research result, it assists in increasing the usage of e-banking services by providing relevant guidance that encourages wider adoption. Furthermore, it enhances customer retention by providing additional value through accurate and beneficial recommendations. Thus, it enables banks to understand customer behavioural patterns, facilitating the delivery of more personalized suggestions tailored to their specific needs.

5 Conclusion

E-banking transaction services for purchases and payments encompass various products, such as fund transfers, bill payments, balance inquiries, and other banking activities accessible through the Internet or mobile banking applications. E-banking transaction services are highly sought after by customers due to their convenient accessibility, time-saving benefits, and flexibility. Users appreciate the ability to perform diverse transactions without the need to visit a physical bank office. The growing popularity of this service is further attributed to its advanced security features, which enhance user confidence and satisfaction. By selecting the best clustering method, BIRCH, which provides the highest accuracy compared to other methods, namely Minibatch K-Means and K-Means, is applied to obtain maximum group results to see the evaluation results of processing e-banking service transaction data. From the results of this research, there are services whose promotion needs to be increased, including the use of Deposits, OVB, and ATB Transfers. Some of these services can be used as a reference by the bank to improve promotions so that all services can be used and utilized well by customers, thereby increasing the value of the bank's services. However, this research can be enhanced by using other methods for grouping similar items or entities based on certain characteristics or features. In addition to its application in e-banking services, clustering can be employed in different domains for various purposes.

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