Journal of Theoretical and Applied Information Technology
15th August 2021. Vol.99. No 15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BI DASHBOARD TO SUPPORT DECISION MAKING ON PRODUCT PROMOTION FOR PAYMENT/PURCHASE TRANSACTIONS ON E-BANKING

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ABSTRACT

Product promotion is one of the business strategies expected to make customers use e-banking in every transaction process. Therefore, the bank must adjust the customer expectations and provide suitable services based on transaction history to increase the use of e-banking. One of the solutions with the right approach to such a problem is creating a smart Business Intelligence system that comes in BI Dashboard. By highlighting the key performance and indicators of transactional data, managers are expected to gain information or insights that can be used as a reference to give more accurate promotions. Finally, cluster analysis using the K-Means algorithm is also provided to group data against its respective characteristics that may have been unnoticed. Then, stakeholders can translate the characteristics of each cluster into their business perspective. Based on the test results by comparing two samples from the pretest and posttest results (paired T-Test), the knowledge value of the management team after implementing the BI Dashboard increased to 95.2%. Therefore, the BI Dashboard with the K-Means algorithm is the suitable method to be applied as a decision making for e-banking product promo recommendations for payment and purchase transactions.

Keywords: *Business Intelligence, E-Banking, K-Mean, Product Promotion, Transaction Data*

1. INTRODUCTION

The fast movement of technology in the banking sector provides convenience for customers to conduct financial transactions more efficiently. One of the transaction methods which came into wide use is e-banking. By definition, e-banking is an internet portal that allows customers to use various banking services from bill payments, balance reports, transfers until making investments [1]. E-banking consists of Mobile Banking and Internet Banking.

The number of e-banking users in Indonesia in 2019 has increased compared to previous years. It leads to the creation of programs by the bank that appeal to loyal customers, such as providing various promos [2][3][4]. This promo is one of the business strategies expected to make customers use e-banking in every transaction process. However, this promo strategy will be useless if not executed properly. Therefore, the bank must adjust the customer expectations and provide suitable services based on transaction history to increase the use of e-banking. Besides, the increased number of e-banking users can impact the increased number of e-banking transaction data.

PT XXX is a banking company with customers spread throughout Indonesia. Currently, all the data collection processes, data visualization, and promotion decisions by PT XXX are still made manually by using Microsoft Excel and Pivot Table. Based on the interviews with the management of PT XXX, there are several problems related to the promotion decisions, including: (1) The data obtained from Microsoft Excel is still in the form of raw data, and it takes time to process it into useful information, (2) The limited data that can be stored and processed in Microsoft Excel makes the monitoring process inefficient, and (3) The reporting process takes a long time until it gets to the management. Previous researchers proposed a business intelligence system for banking performance based on product analysis to determine the best deal product for customers [1][5]. Business Intelligence (BI) can perform data transformation from raw data into useful information or insight that supports company decision-making and business processes [6][7]. A BI system will be developed as a decision-making product promo for payment/purchase transactions at PT XXX in this research. We will evaluate the research results through usability and functionality testing.

The use of BI in business is intended as a tool for business analysts by using data visualization methods to gain knowledge from data stored in structured databases [7][1]. Data visualization comes in the form of a visual panel (dashboard) that presents information that is accessible even to people from non-data specialists. This dashboard can help in analyzing and understanding performance from the past and can also be used to forecast future strategies to improve key performance indicators of current business strategies.

As previously stated, the higher the number of users using e-banking, it will also affect the increase in the number of transaction data in e-banking [1][8]. Thus, the raw transaction data (payment/purchase) will always grow and can become big data or can be called big data [8]. However, these data enhancements can often be imprecise, uncertain, ambiguous, and incomplete. Therefore, to assist the process of analyzing payment/purchase transaction data to extract knowledge from the data in making decisions that are more meaningful, efficient, and effective, this study proposes using the clustering method. Some of this research explained that the K-Means clustering method had become an affection tool for banking sector analysis. The application of K-Means to e-banking transaction data has been successfully used for customer segmentation [9] and helps decision-makers predict in improving the banking industry [10]. Furthermore, this method can handle a large number of datasets with low complexity and low computation time [9][11][12][13]. Therefore, we use K-Means clustering to support the decision to provide promos for payment/purchase transactions in e-banking.

In this study, the data warehouse stores extensive data in the repository. Data mining is processed using the clustering method to extract knowledge from the transaction data to get new data presented to BI, which is used to assist in supporting decision-making. It was also found in research [14][15] so that the information is used to support the decision to provide product promos for payment/purchase transactions in e-banking. It will also make the system smarter to provide solutions related to the company's business needs. We hope that through this research, the BI dashboard system can help process customer transaction data easily and quickly to provide promo recommendations and assist banking management in making decisions related to marketing.

2. BACKGROUND AND RELATED WORK

2.1 Business Intelligence

Business Intelligence (BI) is a set of processes, architectures, and technologies that converts raw data into useful information in the form of reporting, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, analytical prediction, and analytical computing in order to support business decisions [7][16][17][18]. Based on the previous researchers, BI is a process, technology tool that can transform data into information, information into meaningful knowledge used to plan a corporate strategy for profit.

Prayitno [1] proposed the BI system for banking performance based on product analysis. This system can help corporate leaders make decisions related to developing a potential bank product that provides excellent benefits. With dashboard reporting displayed, the performance of the bank of the various products offered and the decision-making process implemented quickly and accurately. PT XXX needs this BI system to provide valid and actual monitoring information to assist the company management in making promotion decisions. One crucial component to support the process is the visualization through a computerized dashboard commonly used as the primary information delivery process for getting BI information to assist the company management [19].

2.2 K-Means Algorithm

The transaction data can be used to get a deeper understanding of customers, market segmentation, and targeted marketing [1][8]. This number of transaction data increased year-to-year, affected by increased banking users [2][4]. Due to this, several research works have been undertaken related to the banking sector. Within these studies, clustering has become an affection tool for analyzing the banking sector [1][10]. This method can handle a large number of datasets, low complexity, and low computation time [11][12][13]. K-means algorithm is an iterative algorithm, part of unsupervised learning, which tries to partition the dataset into K pre-defined distinct non-overlapping subgroups (clusters) [20]. Besides, it is used to make the intra-cluster data points as close as possible while also keeping the cluster as far as possible. It aims to minimize the cluster performance index, square error, and error criterion, which is the basis of this method. The K-means method can work with the following processes [13]:

a. It accepts the number of clusters to group data and datasets into clusters as input values.
b. Initialize the first K cluster (take the first k sample or take a random sample of k elements).
c. Calculate the arithmetic mean of each cluster formed in the dataset.
d. K-means assigns each record in the dataset to only one initial cluster (each record is given to the nearest cluster using a distance measure, e.g., Euclidean distance).
e. K-means reassign each record in the dataset to the most similar cluster and recalculate all clusters' arithmetic mean in the dataset.

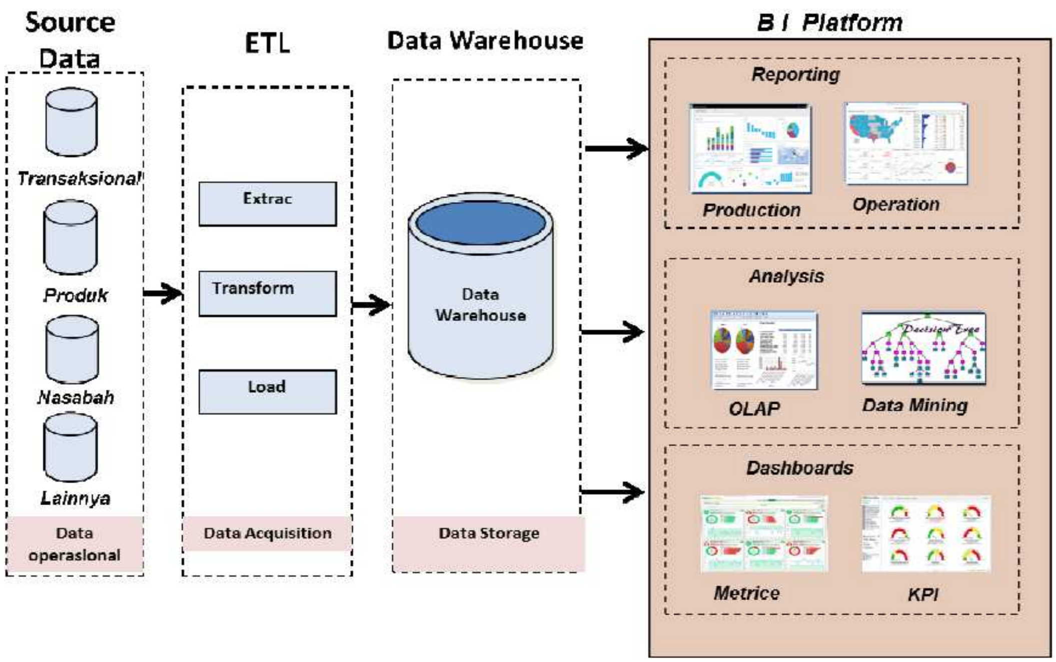

Figure 1: BI Framework Prayitno [1]

3. MATERIALS AND METHODS

This section will formulate the material and methodology for the proposed work to deal with large-scale transaction data, low computation time, and automation in determining promotion for e-banking customers. Then, the BI dashboard is presented. Finally, the clustering method, the K-means algorithm, is proposed to provide valid and actual monitoring information that can assist the company management in making promotion decisions. Figure 2 illustrates the proposed model of the BI dashboard to support decision-making on product promotion for payment or purchase transactions on e-banking.

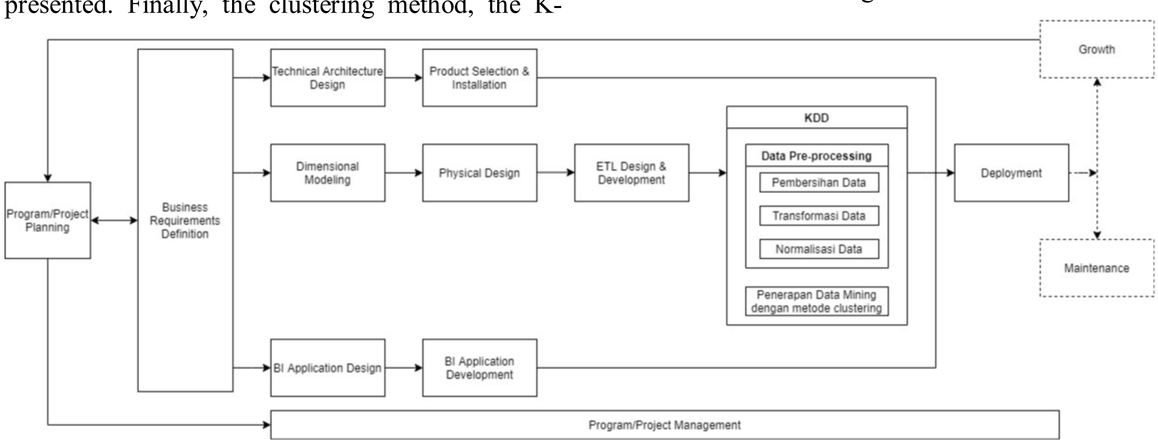

Figure 2: BI Dashboard architecture with clustering method

3.1 Data Source

The dataset being used in this research is raw financial data of e-banking (internet and mobile banking) from PT XXX from 2016 to 2020. This dataset contains customer-related data, transactional data, and product data. Transactional data is recorded in every transaction process, such as sales, sales orders, purchase orders, delivery orders, and quotations. Customer data is data that includes all customer-related data and products purchased. Table 1 shows an example of e-banking data.

Table 1: PT XXX e-banking data sample

ServiceName	TanggalTransaksi	BiayaAdministrasi	TotalJumlah	Regional	Nominal
Bill Payment	2016-01-24	0.0	11000000.0	Medan	11000000.0
Interbank transfer	2016-01-04	6500.0	5006500.0	Jakarta 2	5000000.0
Overbooking	2016-01-20	6500.0	256500.0	Jakarta 2	250000.0
Interbank transfer	2016-01-17	6500.0	56500.0	Jakarta 2	50000.0
....	…	...	...	...	...
Interbank transfer	2016-01-14	6500.0	156500.0	Jakarta 2	150000.0

ServiceName is a type of transaction made by a customer. TanggalTransaksi is the date recorded when the customer makes a transaction. Then, BiayaAdministrasi is administrative costs imposed by banks in every transaction made by customers. TotalJumlah is the total amount of funds transacted and additional admin fees incurred by the customer. Regional is the division of administrative areas for branch offices or sub-branch offices in an area at PT XXX. Nominal is the nominal amount of customer transactions made by customers.

3.2 BI Dashboard

This dataset as a data source needs to be processed into the data warehouse, transformed, and loaded through the system into a single data warehouse table. Therefore, this dataset is made of logical data modeling from one dimension to multidimensional in a data mart or cube to make it easier in the following data process. In this phase, the data source will be integrated into a data warehouse through the ETL (Extract, Transformation, Load) process.

3.3 Knowledge Discovery

Data mining, commonly known as knowledge discovery in database (KDD), is a set of activities covering the entire data process from collecting to finding regularities, patterns, or relationships in large historical data sets and any processes in between [21]. Thus, the KDD can be explained as follows [22]: (1) Data Selection, raw data must be selected before the information mining stage begins, (2) Data Pre-processing/cleaning, including removing duplication of data, checking inconsistent data, correcting errors (such as typos) and enriching data with other relevant information, (3) Data Transformation, the process of transforming the data format to suit the input from data mining, (4) Data mining, the primary process is finding useful information or patterns in selected data using specific methods, and (5) Interpretation/Evaluation, the process of examining patterns or information found and comparing them with previous hypotheses.

3.4 Deployment

In this phase, checking the patterns or information found and comparing them with the previous hypothesis will be carried out. This evaluation process is carried out to obtain information on the usability and functionality of the BI dashboard system. This process will include Usability Testing and Functional Testing processes.

At the stage of the application development, it will be implemented and introduced to the user. The next step is to evaluate the usability of the system using a usability questionnaire. Usability testing aims to measure effectiveness, efficiency, convenience, and user satisfaction in using the BI Dashboard system with the K-Means method. The scale used in this test is the Likert scale which consists of five criteria in Table 2.

Table 2: Likert scale

Scale	Criteria
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly agree

BI Dashboard needs to be improved so that efficiency, ability to detect errors, be controlled,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

meet user satisfaction, learnability, flexibility, visibility, and application behavior because these criteria still have low ratings or are included on a large scale for improvement questionnaire data. Besides, indicators of learnability (from the user's point of view), memorability, and decision support are included in the priority category for improvement. Therefore, Usability testing is needed to get an idea of using the BI Dashboard for users. In studying the indicators used in usability testing, they apply the indicators shown in Table 3 [23].

Table 3: Usability Testing Indicators

Aspect	Indicator
Learnability	Easy to understand its use, easy to use to find specific data, easy to identify navigation utility
Memorability	Easy to remember, Easy to reuse
Efficiency	Easy to reach quickly, showing good navigation
Error Detected	Displays informative error messages, Errors can be fixed effortlessly
User's Satisfaction	Fun system to use, Comfortable to use

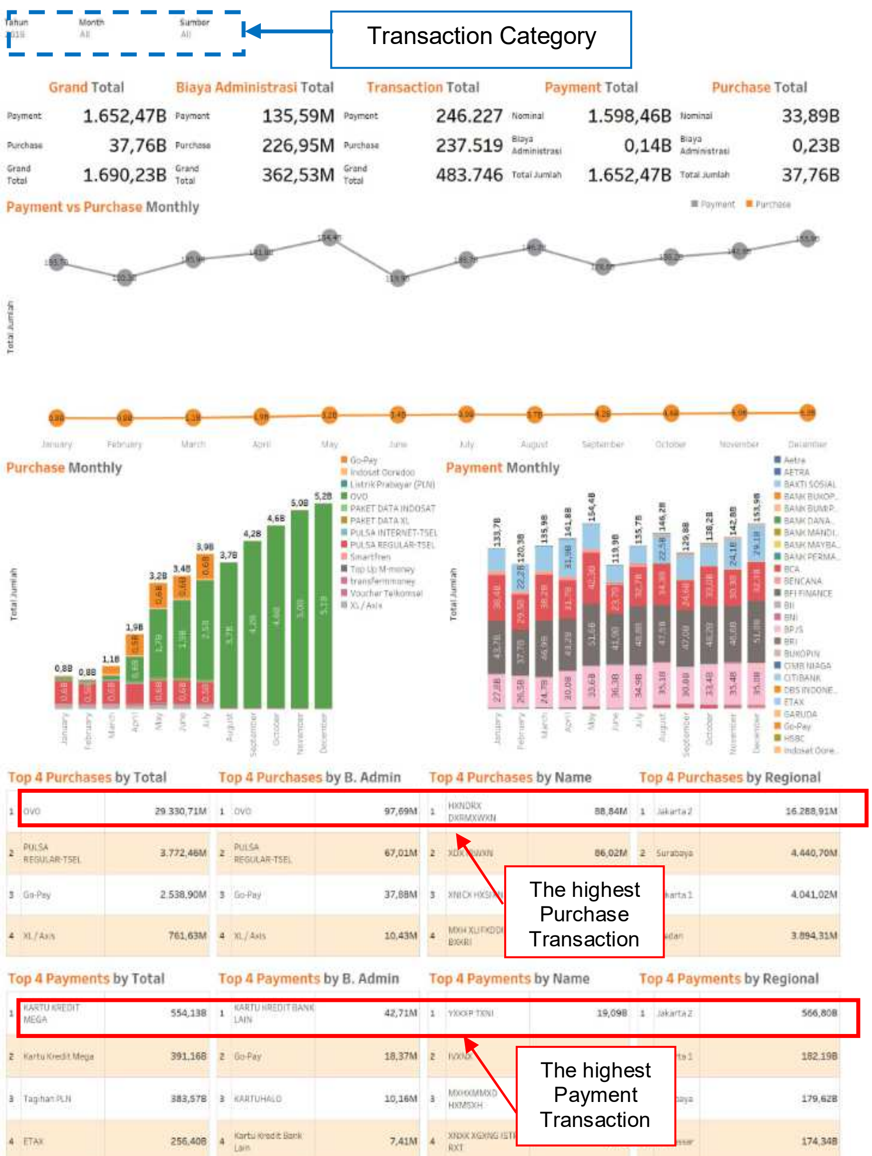

Figure 3: BI Dashboard created using Tableau

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4. RESULTS AND DISCUSSIONS

4.1 BI Dashboard Implementation

The BI dashboard is a report designed as a summary and visualization of data using Tableau. Report generated from the Mobile Banking and Internet Banking transactions dataset for the past five years in 2016-2020. This data visualization is used to facilitate understanding of the management team by communicating existing transaction data. Figure 3 depicts the BI dashboard created using Tableau.

The decision to provide a minimum promo based on the highest number and total transactions has been fulfilled, which can be seen through the display on the BI dashboard in Figure 3. The display also provides details for each transaction category available in Year, Month, and Source of Income (internet banking or mobile banking). In this case, the management at the company must make decisions in product promotion easier, efficiently, and effectively. The BI Dashboard allows company management to receive customizable reports because it is easier to access and understandable. In this study, the report contains the highest number of transactions, the most increased purchases, and customer transactions.

4.2 Transactional Data Clusters using K-Means Algorithm

Since K-Means requires K as an amount of the data group, there is no correct answer in terms of determining the K value. However, several methods are usually used, such as calculating the sum of squared distance (SSE) between data points and their assigned clusters' centroids, known as the Elbow Method. The idea behind the Elbow method is picking the K value at the spot where SSE starts to flatten out and forming an elbow. This method can determine the number of groups by comparing the increase in the K value (number of groups) against the distance/distortion magnitude. The K value (number of groups) selected is the last K value, which significantly changes the distance/distortion. This clustering process has been successfully tested using python programming.

4.2.1 Data Selection

Raw data needs to go through the selection stage before processing to the next process. There are 8 attributes selected for the clustering process with a large total number of data rows 1,836,664. The attributes chosen are based on the column in the data table which contains BiayaAdministrasi, NamaInstansi, NamaPemilikRekening, Nominal, Regional, Service Name, Sumber, and TotalJumlah. The selected attributes will later be used as parameters for further data processing.

4.2.2 Data Pre-processing

The results of data selection (selected data) will be going to the data pre-processing, which includes removing duplication of data, checking for inconsistent data, correcting errors (such as typos), and enriching the data with other relevant information. The data before pre-processing is shown in Figure 4.

```
BiayaAdministrasi      237994
NamaInstansi                0
NamaPemilikRekening      1525
Nominal                     9
Regional                    0
ServiceName                 0
Sumber                      0
TotalJumlah                 0
dtype: int64
```

Figure 4: Inconsistent amount of data

This data pre-processing will be carried out to clean inconsistent data such as several null data. There are many options for filling in null data origin done consistently. In this study, null data will be filled in with the data that has the largest amount. The data after pre-processing is shown in Figure 5.

```
DatetimeIndex: 1836655 entries, 2016-01-01 00:00:00 to 2020-09-30 23:18:56
Data columns (total 8 columns):
 #   Column               Dtype
---  ------               -----
 0   BiayaAdministrasi    float64
 1   NamaInstansi         object
 2   NamaPemilikRekening  object
 3   Nominal              float64
 4   Regional             object
 5   ServiceName          object
 6   Sumber               object
 7   TotalJumlah          float64
dtypes: float64(3), object(5)
memory usage: 126.1+ MB
```

Figure 5: The results of pre-processing data

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.2.3 Data Mining

Data mining is a process of obtaining useful information from large database warehouses. Data mining can extract new information drawn from large chunks of data that help in decision-making. This study utilized one of the analytical techniques to trace the data in building a model to recognize patterns from the data so that data mining could use it to find out the subsequent follow-up to be taken. As in this study, as decision support for product promotion recommendations from the banking company PT XXX.

This clustering method is used as a prototype of the most representative group of data, providing an abstraction of all data objects in the group where data is located. For example, a banking company usually has a large amount of information about all transaction data. This clustering process can be applied to break down transaction data into small groups for analysis and marketing strategies. In this study, the use of K-Means is to attempt to partition existing data into two or more groups. In this phase, the K-Means method requires K as the number of groups of data. There is no correct answer to determine the value of K. However, several methods are commonly used, such as calculating the Sum of Squared Distance (SSE) between the data points and the defined cluster centroids known as the Elbow method. The idea behind the Elbow method is to choose the K value at the point where the SSE starts to flatten and form the elbow. This method can determine the number of groups by comparing the increase in the value of K (number of groups) to the distance/amount of distortion. The K value (number of groups) selected is the last K value that significantly changes distance or distortion.

The K-Means method uses the euclidean distance principle because it calculates the distance between two points, where each point is represented in multidimensional. The Euclidean distance principle is suitable for data with a small number of variables and relatively short data so that all columns must have an integer or float data type. Regional, Sumber, and NamaInstansi have a string data type, so it needs to be converted into an integer without losing the information inside using one-hot encoding. Figure 6 shows the results of the euclidean distance process in one of the categories, namely purchase.

```
DatetimeIndex: 846473 entries, 2016-01-20 20:39:32.647000 to 2020-09-30 23:18:56
Data columns (total 28 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   BiayaAdministrasi             846473 non-null  float64
 1   NamaPemilikRekening           846473 non-null  object
 2   Nominal                       846473 non-null  float64
 3   TotalJumlah                   846473 non-null  float64
 4   Regional_Bandung              846473 non-null  uint8
 5   Regional_Banjarmasin          846473 non-null  uint8
 6   Regional_Jakarta 1            846473 non-null  uint8
 7   Regional_Jakarta 2            846473 non-null  uint8
 8   Regional_Makassar             846473 non-null  uint8
 9   Regional_Medan                846473 non-null  uint8
 10  Regional_Semarang             846473 non-null  uint8
 11  Regional_Surabaya             846473 non-null  uint8
 12  Sumber_Mobile Banking         846473 non-null  uint8
 13  NamaInstansi_ESIA             846473 non-null  uint8
 14  NamaInstansi_EWALLET          846473 non-null  uint8
 15  NamaInstansi_GOPAY            846473 non-null  uint8
 16  NamaInstansi_Indosat Ooredoo  846473 non-null  uint8
 17  NamaInstansi_OVO              846473 non-null  uint8
 18  NamaInstansi_PAKET DATA INDOSAT  846473 non-null  uint8
 19  NamaInstansi_PAKET DATA XL    846473 non-null  uint8
 20  NamaInstansi_PLN PRABAYAR     846473 non-null  uint8
 21  NamaInstansi_PLN PREPAID      846473 non-null  uint8
 22  NamaInstansi_PULSA INTERNET-TSEL  846473 non-null  uint8
 23  NamaInstansi_PULSA REGULAR-TSEL  846473 non-null  uint8
 24  NamaInstansi_SMARTFREN        846473 non-null  uint8
 25  NamaInstansi_Top Up M-money   846473 non-null  uint8
 26  NamaInstansi_XL / Axis        846473 non-null  uint8
 27  NamaInstansi_transfermmoney   846473 non-null  uint8
dtypes: float64(3), object(1), uint8(24)
memory usage: 51.7+ MB
```

Figure 6: Display data attributes of the purchase category

The value of K (number of groups) selected is the last K value, which significantly changes distance or distortion. Figure 7 shows that the value of k above four does not offer a significant difference anymore, so choosing K = 4 could be the right choice. To determine the training and testing dataset distribution using the random_state parameter, if we do not specify random_state, every time you run the code, a new random value will appear generated from the training. As a result, the testing dataset will have a different value. However, if a value is set like random_state = 42, no matter how many times you run the code, the result will be the same, i.e., the same value in the training and testing dataset.

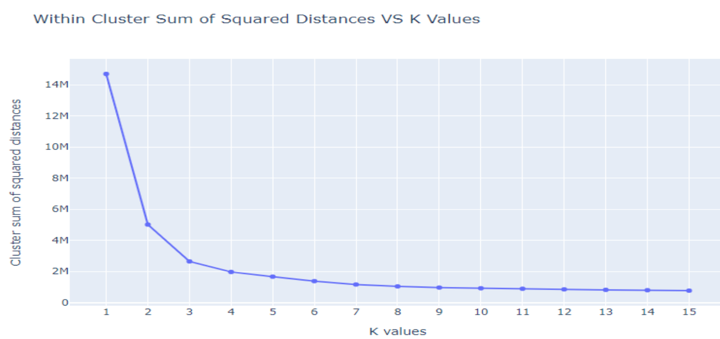

Figure 7: Cluster sum of squared distances vs. K values

From the 4 groups that have been determined, the results of the average characteristics of each group can be seen in Figure 8.

Cluster	BiayaAdministrasi	Nominal	TotalJumlah	log_Regional_Semarang	log_Regional_Surabaya	log_Sumber_Mobile Banking	log_NamaInstansi_ESIA
0	814.649271	36555.829364	38910.810709	0.053070	0.094360	0.693359	0.000235
1	1155.134306	120555.329391	124943.600744	0.043701	0.088440	0.693359	0.000004
2	916.476019	722312.174534	751632.486456	0.048309	0.105408	0.693359	0.000000
3	1429.666898	35931.418477	37361.085375	0.040741	0.088745	0.693359	0.000000

Figure 8: Clustering result sample of transaction purchase data with 4 cluster

Besides, the distribution of data according to clusters can at most be displayed by 3-dimensional graphics. There are many attributes (features) that represent a data set. Figure 8 shows a sample data group based on the TotalJumlah, NamaInstansi, and Regional. From this graph, it can be seen that in Regional, the two most purchased transactions based on the highest total amount.

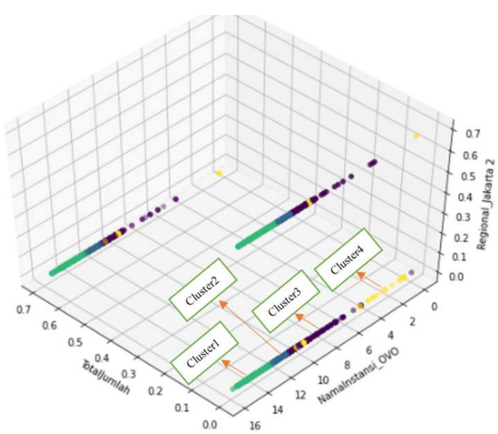

Figure 9: Sample of data scatters in 3-dimensional graphics

There are 4 clusters with the following per cluster distribution:

a. Cluster 1: BiayaAdministrasi, NamaInstansi, NamaPemilikRekening, Nominal, Regional ServiceName, Sumber, TotalJumlah.
b. Cluster 2: BiayaAdministrasi, NamaPemilikRekening, Nominal, TotalJumlah, Regional, Sumber_Mobile Banking.
c. Cluster 3: BiayaAdministrasi, NamaPemilikRekening, Nominal, TotalJumlah, Regional, Sumber_Internet Banking.
d. Cluster 4: BiayaAdministrasi, NamaPemilikRekening, Nominal, TotalJumlah, Regional, Nama Instansi.

4.3 Evaluation and Validation

This usability test was carried out by two respondents who were the Dept. Head and Group Head IT at PT XXX. The purpose of usability testing is to measure the level of effectiveness, efficiency, convenience, and user satisfaction in using the BI Dashboard system with K-Means using a Likert scale. The results of the test can be seen in Table 4.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4: The result of Usability Testing

No.	Questions	Respondent 1 (Dept. Head)	Respondent 2 (Group Head)
1.	I think that I would like to use this system	5	4
2.	I found the system unnecessarily complex	1	3
3.	I thought the system was easy to use	5	4
4.	I think that I would need the support of technical person to be able to use this system	1	2
5.	I found the various functions in the system were well integrated	5	4
6.	I thought there was too much inconsistency in this system	1	1
7.	I would imagine that most people would learn to use this system very cumbersome to use	1	3
8.	I felt very confident using the system	5	4
9.	I needed to learn a lot of things before I could get going with this system	1	1

This evaluation and validation process is the final stage by testing the BI Dashboard with the K-Means algorithm. The pretest result shows that the respondents have analyzed the data to compile daily, monthly, and annual reports using Microsoft Excel. The score obtained from the pretest and posttest results is then used as a variable in the T-Test. The T-test used in this study was the paired T-test (two independent variables). The T-test aims to compare (differentiate) whether the two variables are the same or different. The point is to test the generalizability (the significance of the research results in comparing two sample averages). Paired T-test was conducted to test differences in knowledge of respondents before and after using the BI Dashboard (1 division team at PT XXX). The results of the pretest and posttest scores are represented in Table 5.

Table 5: Pretest and posttest score

Respondent	*Pretest*	*Posttest*
1	26	100
2	40	100
3	20	78
4	50	100
5	20	98

This test is helpful for testing two samples that are interconnected or correlated or called "paired samples" from populations that have the same average. For example, the results of the Paired Sample T-Test using SPSS can be seen in Figure 10.

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Pretest	31.2000	5	13.31165	5.95315
	Posttest	95.2000	5	9.65401	4.31741

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Pretest & Posttest	5	.523	.366

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	Pretest - Posttest	-6.400E1	11.66190	5.21536	-78.48017	-49.51983	-12.271	4	.000

Figure 10: Paired sample T-Test result

Figure 10 shows the average difference (mean) between the knowledge value of the management team before using the BI Dashboard (X1) of 31.2 with five respondents and Std. Deviation (standard deviation) of 13.311. Meanwhile, the knowledge value of the management team after using the BI Dashboard

(X2) was 95.2 with five respondents and Std. Deviation (standard deviation) of 9.654.

In addition, Figure 10 shows the magnitude of the correlation between X1 and X2, which is 0.523 with a significance level of 0.366.
The hypothesis:

Ho: *<u>There is an increase</u> in the value of knowledge from the management team after implementing the BI Dashboard to help make decisions on recommendations for e-banking product promos.*

Ha: *<u>There is no increase</u> in the value of knowledge from the management team after implementing the BI Dashboard to help make decisions on recommendations for e-banking product promos.*

Decision rule:
If α = 0.05 is less than or equal to the Sig value. Or [α = 0.05 ≤ Sig], then Ho is accepted, and Ha is rejected. If α = 0.05 is less than or equal to the Sig value. Or [α = 0.05 ≥ Sig], then Ha is accepted, and Ho is rejected.
It turns out that α = 0.05 is smaller than the significance value (Sig) or [0.05 <0.366], so Ho is accepted, and Ha is rejected. Therefore, it can be interpreted that there is an increase in the value of knowledge from the management team after implementing the BI Dashboard to assist data analysis and decision-making on the recommendation of e-banking product promos.
Figure 10 also shows the t_{count} value of -12.271 with a significance level of Sig. (2-tailed) = 0.000 with a df (degree of freedom) value of 4 (N-1). Determination of the t_{table} value can be found based on the df value and significance value (α / 2). Hence, it can be obtained that the t_{table} value is 2.571 at the significance level [α = 0.05 / 2] from the t_{table} statistical value distribution table. It can also be used to decide whether the proposed hypothesis is accepted or rejected with the following decision rules:

If $t_{count} \geq t_{able}$ then Ha is accepted and Ho is rejected, otherwise if $t_{count} \leq t_{able}$ then Ho is accepted, and Ha is rejected.

It turns out that $t_{count} < t_{tabel}$ or -12.271 <2.571, then Ho is accepted, and Ha is rejected. So, it can be interpreted that there is an increase in the knowledge value of the management team after implementing the BI Dashboard to assist data analysis and decision making on the recommendation of e-banking product promos or there are differences between the two variables being compared.

4.4 Discussion

In this research, the main focus is creating a Business Intelligence system at PT XXX as a decision supporter to provide product promos for payment/purchase transactions in e-banking. Previously, PT XXX, in determining e-banking promos, only used the Microsoft Excel application. Of course, this process took quite a long time. Then, we evaluate using usability and functionality testing. Before the BI Dashboard system, only 31.2% knew management. After using BI Dashboard, management knowledge increased 64% to 95.2%. Figure 11 shows a comparison chart before and after using the BI dashboard.

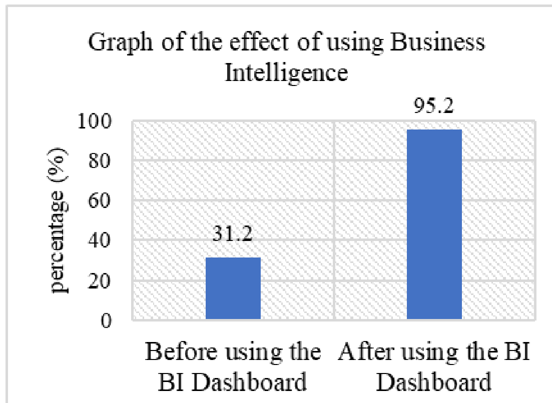

Figure 11: The result graph of using Business Intelligence

BI Dashboard and cluster analysis have been successfully developed to provide better promotional decisions. The dashboard shows the complete analysis of the data highlighting the highest transactions in number and total. Then a clustering algorithm, K-Means used to group data into their closest characteristics. There are 4 clusters in the entire data based on an elbow method. In addition, stakeholders can translate the features of each cluster into their business perspective and are expected to provide more accurate promotions based on the distribution of purchase and payment transaction data. Based on the test results by comparing two samples from the pretest and posttest results (paired T-Test), the knowledge value of the management team after the BI Dashboard significantly increased. Therefore, it can be concluded that the results of this study, the BI Dashboard with the K-Means algorithm, is the correct method to be applied as a decision making for e-banking product promo recommendations for payment and purchase transactions at PT XXX.

5. CONCLUSIONS

The use of e-banking by customers in Indonesia is increasing day by day. Even in one day, millions of transactions can occur through e-banking. The management must process and visualize a large amount of data to obtain decisions, one of which is promos. Processing that much data, of course, requires special techniques, which certainly make it easier for management to determine promo decisions. Using the BI Dashboard with the K-Means method is proven to handle extensive data processing compared to manually using Microsoft Excel. It is proven that management knowledge with the BI Dashboard has increased by 64%. This improvement makes it more informative and can use the result in urgent needs.

Future work can be given regarding the BI Dashboard with the K-Means method that has been made is that it can be implemented in the form of a web-mobile to be accessed anytime and anywhere. Then, the recommendation process on processes other than transaction data in the banking domain can be implemented in different fields.

REFERENCES

[1] D. Prayitno, "Application of Business Intelligence for Banking Performance Based on Products Analysis," *Int. J. Progress. Sci. Technol.*, vol. 6, no. 2, pp. 554–569, 2018.

[2] D. M. Hutauruk and N. Laoli, "Transaksi mobile dan internet banking di sejumlah bank meningkat tajam," *kontan.co.id*, 2019. https://keuangan.kontan.co.id/news/transaksi-mobile-dan-internet-banking-di-sejumlah-bank-meningkat-tajam (accessed Apr. 17, 2021).

[3] F. N. Ulya and S. R. D. Setiawan, "Gubernur BI: Selama Pandemi, Transaksi Digital Naik 37,8 Persen," *Kompas.com*, 2020. https://money.kompas.com/read/2020/09/29/154300526/gubernur-bi--selama-pandemi-transaksi-digital-naik-37-8-persen (accessed Apr. 17, 2021).

[4] A. Googie and E. Djumena, "Terus Meningkat, Transaksi 'E-banking' di Indonesia Capai Rp 6.447 Triliun," *Kompas.com*, 2015. https://money.kompas.com/read/2015/09/14/144905526/Terus.Meningkat.Transaksi.e-Banking.di.Indonesia.Capai.Rp.Rp.6.447.Triliun (accessed Apr. 17, 2021).

[5] F. Suprata, "Data Storytelling with Dashboard: Accelerating Understanding through Data Visualization in Financial Technology Company Case Study," *J. Metris*, vol. 20, pp. 1–10, 2019.

[6] P. F. Kurnia and Suharjito, "Business Intelligence Model to Analyze Social Media Information," *Procedia Comput. Sci.*, vol. 135, pp. 5–14, 2018, doi: 10.1016/j.procs.2018.08.144.

[7] N. Ain, G. Vaia, W. H. DeLone, and M. Waheed, "Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review," *Decis. Support Syst.*, vol. 125, p. 113113, 2019, doi: https://doi.org/10.1016/j.dss.2019.113113.

[8] K. Krishnan, "7 - Banking industry applications and usage," K. B. T.-B. B. D. A. Krishnan, Ed. Academic Press, 2020, pp. 127–144.

[9] M. Aryuni, E. D. Madyatmadja, and E. Miranda, "Customer Segmentation in XYZ Bank Using K-Means and K-Medoids Clustering," in *2018 International Conference on Information Management and Technology (ICIMTech)*, 2018, pp. 412–416, doi: 10.1109/ICIMTech.2018.8528086.

[10] K. Bansal and A. Bohra, "K-Mean Clustering Algorithm Implemented To E-Banking," *Int. J. Eng. Res. Technol.*, vol. 2, no. 4, pp. 1644–1650, 2013.

[11] E. Aytaç, "Unsupervised learning approach in defining the similarity of catchments: Hydrological response unit based k-means clustering, a demonstration on Western Black Sea Region of Turkey," *Int. Soil Water Conserv. Res.*, vol. 8, no. 3, pp. 321–331, 2020, doi: https://doi.org/10.1016/j.iswcr.2020.05.002.

[12] P. Govender and V. Sivakumar, "Application of k-means and hierarchical clustering techniques for analysis of air pollution: A review (1980–2019)," *Atmos. Pollut. Res.*, vol. 11, no. 1, pp. 40–56, 2020, doi: https://doi.org/10.1016/j.apr.2019.09.009.

[13] J. Saha and J. Mukherjee, "CNAK: Cluster number assisted K-means," *Pattern Recognit.*, vol. 110, p. 107625, 2021, doi: https://doi.org/10.1016/j.patcog.2020.107625.

[14] Mashudi, N. Rachmawati, T. Suranto, and I. Dwinovita, "Business intelligence system for operational decision making support: A case study on lube distribution," in *2016 International Conference on Data and*

Software Engineering (ICoDSE), 2016, pp. 1–6, doi: 10.1109/ICODSE.2016.7936149.

[15] S. M. Kumar and M. Belwal, "Performance dashboard: Cutting-edge business intelligence and data visualization," in *2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, 2017, pp. 1201–1207, doi: 10.1109/SmartTechCon.2017.8358558.

[16] H. Al-Aqrabi, L. Liu, R. Hill, and N. Antonopoulos, "Cloud BI: Future of business intelligence in the Cloud," *J. Comput. Syst. Sci.*, vol. 81, no. 1, pp. 85–96, 2015, doi: https://doi.org/10.1016/j.jcss.2014.06.013.

[17] K. K. Halim, S. Halim, and Felecia, "Business Intelligence for Designing Restaurant Marketing Strategy: A Case Study," *Procedia Comput. Sci.*, vol. 161, pp. 615–622, 2019, doi: https://doi.org/10.1016/j.procs.2019.11.164.

[18] M. R. Llave, "Business Intelligence and Analytics in Small and Medium-sized Enterprises: A Systematic Literature Review," *Procedia Comput. Sci.*, vol. 121, pp. 194–205, 2017, doi: https://doi.org/10.1016/j.procs.2017.11.027.

[19] J. Reinking, V. Arnold, and S. G. Sutton, "Synthesizing enterprise data through digital dashboards to strategically align performance: Why do operational managers use dashboards?," *Int. J. Account. Inf. Syst.*, vol. 37, p. 100452, 2020, doi: https://doi.org/10.1016/j.accinf.2020.100452.

[20] Z. Huang, "Extensions to the k-Means Algorithm for Clustering Large Data Sets with Categorical Values," *Data Min. Knowl. Discov.*, vol. 2, no. 3, pp. 283–304, 1998, doi: 10.1023/A:1009769707641.

[21] M. Wibowo, F. Noviyanto, S. Sulaiman, and S. M. Shamsuddin, "Machine learning technique for enhancing classification performance in data summarization using rough set and genetic algorithm," *Int. J. Sci. Technol. Res.*, vol. 8, no. 10, pp. 1108–1119, 2019.

[22] Z.-Z. Long, G. Xu, J. Du, H. Zhu, T. Yan, and Y.-F. Yu, "Flexible Subspace Clustering: A Joint Feature Selection and K-Means Clustering Framework," *Big Data Res.*, vol. 23, p. 100170, 2021, doi: https://doi.org/10.1016/j.bdr.2020.100170.

[23] R. Magdalena, Y. Ruldeviyani, D. I. Sensuse, and C. Bernando, "Methods to Enhance the Utilization of Business Intelligence Dashboard by Integration of Evaluation and User Testing," in *2019 3rd International Conference on Informatics and Computational Sciences (ICICoS)*, 2019, pp. 1–6, doi: 10.1109/ICICoS48119.2019.8982481.