## **Evaluation of ATM Location Placement Using the K-Means Clustering in BNI Denpasar Regional Office**

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#### ABSTRACT

The existence of an ATM location requires a placement evaluation that aims to support business and provide convenience and comfort to customers when using or transacting. This study aims to evaluate the placement of ATM locations using the K-Means method and research using data from data mining to obtain decisions that lead to un strategic, strategic, and very strategic ATM locations. This study uses data sourced from the BNI ATM database and performance data in one semester or six months, namely January to June 2021, as many as 121 ATM locations spread across Bali. The application of the K-Means Algorithm in this study uses 6 clustering criteria, namely ATMs Usage, ATMs Fee-Based Income/ FBI, ATMs Service Level Agreement/ SLA, ATMs distance, competitor ATMs, and Business Distance. In addition to presenting calculations using spreadsheets, this research also produces implementations in web-based software. The results of alternative classifications based on K-Means on very strategic centroids of 27 locations or covering 22.31%, strategic several 77 locations or covering 63.64%, and non-strategic 17 locations or covering 14.05%. Although the location of ATMs classified as non-strategic criteria is relatively small, this can be optimized by several strategic steps that stakeholders can take within the company, such as evaluating the bank's business plan in 2022 and improving the supervision of machines at ATM locations.

Keywords: ATMs, BNI, Clustering, K-Means, Strategic.

#### **INTRODUCTION**

Everyone always wants to live life more efficiently and safely in transactions and get the best access to finding strategic positions or specific locations. Determining this or locating strategic locations requires good and correct planning and proper calculations. Competition in the banking industry is currently intensifying, both in terms of delivering product innovations and improving the quality of transactions and services. Banks must find ways to stay competitive and provide customers with excellent banking services, one of which is IT support, which is automated teller machines (ATMs) (Mahendra & Aryanto, 2019). Some of the issues that ATMs have today have become national banking issues. One of the issues Bank Negara Indonesia (BNI) is currently facing is determining the right location to place strategic ATMs for customers. Identifying this location is not easy as several things need to be considered, including the convenience of the site, safety, and commercial potential. Currently, ATM locations are typically set up in crowded places, banking units, and areas of institutions that work with banks. One of the problems that banks face when placing ATMs is ATM vandalism, which affects the bank's losses (Mahendra & Indrawan, 2020). Vandalism damages ATMs, buildings, and equipment, resulting in suboptimal ATM operation, which may reduce ATM usage, performance, and revenue. In addition, an increase in cases of card theft or card cloning can lead to financial damage and loss of integrity in the bank (Mahendra & Subawa, 2019).

BNI is one of the largest banks in Indonesia and a state-owned public institution. They are headquartered in Jakarta and with multiple regional offices from Sabang to Merauke. One of Indonesia's BNI regional offices with significant commercial potential is the Denpasar Regional Office. Transactions by tourists are huge in Bali and daily transactions by the community. Bali and Nusa Tenggara have the highest annual Gross Domestic Product (GDP) growth nationally at 10.3%, with a growth contribution of 3.1% to the national economy. However, of the extensive distribution of ATMs distributed in the city of Denpasar, they still do not have a good analysis of the planning, so there is a need for strategic planning related to the placement of these ATMs. When evaluating the order of this ATM using the K-Means method, which method was used to find the comparison value, the advantage of the K-Means method is that it is relatively easy to implement, it can handle fairly large data, and the time to run the process is fairly fast (Kasim, Bahri, & Amir, 2021). When comparing existing location data, several data selection steps were

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Journal of Computer Networks, Architecture and	
High Performance Computing	Submitted : June 27, 2022
Volume 4, Number 2, July 2022	Accepted : July 13, 2022
https://doi.org/10.47709/cnahpc.v4i2.1580	Published : July 23, 2022

performed using the clustering process to achieve good results in placing ATM sites in strategic locations. The authors can implement this approach with the number of ATMs and areas with different characteristics. The authors identified placement locations on operational ATMs and needed to evaluate ATM locations that were less strategically placed and deemed less or less attractive to customers. Based on the problems described previously, the purpose of this study is the strategic ATM placement evaluation system by implementing the K-Means method. Several previous studies related to the implementation of K-Means Clustering have also been successfully carried out, including for grouping sales data, decision-making of BLT recipients, beef production clustering, and clustering poverty data field (Halawa & Hamdani, 2019; Kusanti & Sutanto, 2021; Pandiangan, 2019; Sugianto & Bokings, 2021). Furthermore, this study also aims to test K-Means' effectiveness in increasing business potential and business benefits in evaluating BNI ATM placements.

#### LITERATURE REVIEW

Data mining is the process of finding hidden patterns from large or large collections of data stored in databases or data warehouses and other data storage locations (Chakraborty, Islam, & Samanta, 2022; Reddy & Suneetha, 2021). Activities include collecting and using data to determine regularity, patterns, or relationships between big and large data. One of the tasks of data mining is to group or cluster data without sample groups. Data mining is also the process of finding valuable correlations, patterns, and emerging trends in big data storage media using pattern recognition techniques such as statistical and mathematical techniques (Hicham, Jeghal, Sabri, & Tairi, 2020). Other terms often used include knowledge mining from data, knowledge extraction, data/pattern analysis, data archaeology, and data dredging (Lisnawati & Sinaga, 2020).

Clustering is dividing a set of data objects into subsets of objects (Petrus, Ermatita, & Sukemi, 2019; Zhu, Wang, & Wang, 2019). Each subset of things is a cluster, so objects in one cluster are similar to each other but not to objects in other clusters. The collection or collection of sets produced by cluster analysis may be referred to as clusters. Different clustering methods may result in different groups of the same dataset. The partitioning process is not performed by humans but by clustering algorithms. Therefore, clustering is very useful because it can discover various previously unknown groups in the data. Clustering has been widely used in multiple applications such as business intelligence, image pattern recognition, image pattern recognition, web search, biology, and security (Rasyid & Andayani, 2018; Yusmartato et al., 2019).

The K-Means algorithm is an algorithm that requires k input parameters and divides a set of n objects into k clusters so that the level of similarity between members in one group is high while the level of similarity with members in other collections is very low (Aldino, Darwis, Prastowo, & Sujana, 2021; Khatami & Suhartana, 2020). The similarity of members to the cluster is measured by the object's proximity to the mean value in the cluster or can be referred to as the cluster centroid or centre of mass. K-Means is a partitional clustering algorithm; that is, it divides the set of data objects into non-overlapping subsets (clusters) so that each data object is in exactly one cluster (Rifa, Pratiwi, & Respatiwulan, 2020). The most frequently used partitional-clustering strategy is based on the square error criterion.

#### METHOD

The proposed model is shown in Figure 1, where the modelling starts from the collection dataset to the validation dataset. At this stage, data preparation can be carried out. Data preparation is data cleaning and data integration, and clustering is carried out after the clustering process is determined. After verifying the correct calculation, the analysis enters the software implementation phase and is tested against the software.



Fig. 1 Proposed Model in Research

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#### **Data Preparation**

This research was conducted at Bank BNI Regional ATMs in Bali, with the object of researching as many as 121 ATM locations. Data preprocessing includes data selection, cleaning, and data transformation steps. This study collects data with 6 supporting research criteria at the data selection stage. At the cleaning stage, a process is carried out to clean the data, namely completing the data, removing duplicate data, and eliminating noise. Cleaning the data is carried out to select good attribute data used in research. The data transformation process is used to format the data so that it is ready for use in each cluster in the study.

The data transformation process can be done by transforming each criterion in the study. In the initial data processing, data processing is carried out on the requirements for the average number of ATM usage as follows. The criteria for the average number of uses or ATM transactions is the first of several measures that influence the placement of ATMs. The requirements for the average number of ATM uses are divided into 3 sub-criteria: high, medium, and low. The criteria for the average amount of income at this ATM location is strongly influenced by the use of ATMs and the performance of ATMs at that location and is divided into 3 sub-criteria, namely very productive, productive and unproductive. ATM service level/performance is a benchmark for ATM activities that serve customer transactions and is divided into 2 sub-criteria, namely optimal and not optimal. On the criteria for the BNI ATM database in 2021. In determining the distance between location points using the Euclidean Distance method formula, which is run on a location processing program using HTML and MySQL programming to obtain distance data between locations, ATMs are similar and are divided into 2 sub-criteria, namely near and far. The criteria for the number of ATMs of competing banks is a criterion that affects the placement of ATM locations because the existing population of ATMs can suppress customer interest in using different ATMs if there are various types of ATMs at that location and divided into 3 sub-criteria, namely very good, good and not good.

#### Clustering

In this study, criteria and classifications or clusters can be determined using the K-Means method to determine the evaluation results of the placement of ATM locations. Here is a step-by-step process showing the K-Means clustering algorithm shown in Figure 2 (Sugianto & Bokings, 2021).



Fig. 2 K-Means Clustering Algorithm

- Step 1. Determine the value of the k = number of clusters
- Step 2. Put any initial partition that classifies the data into k clusters. You may assign the training samples randomly or systematically as follows. Take the first k training sample as single-element clusters. Assign the remaining (N-k) training samples to the group with the nearest centroid. After each assignment, recompute the centroid of the gaining cluster.
- Step 3. Take each sample in sequence and calculate its distance from the centroid of each of the clusters. If a piece is not currently in the group with the closest centroid, switch this sample to that cluster and update the cluster's centroid to gain the new model and the cluster losing the example.
- Step 4. Repeat step 3 until convergence is achieved, that is, until a pass through the training sample causes no new assignments

The application of the K-Means Algorithm in this study uses 6 clustering criteria: ATMs usage, fee-based income (FBI), ATMs service level agreement (SLA), ATMs distance, competitor ATMs, and business distance. All

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Journal of Computer Networks, Architecture and	
High Performance Computing	Submitted : June 27, 2022
Volume 4. Number 2. July 2022	Accepted : July 13, 2022
https://doi.org/10.47709/cnahpc.v4i2.1580	Published : July 23, 2022

of the above criteria determine the evaluation results by grouping the requirements using the clustering method and applying the K-Means algorithm in the study.

In evaluating the placement of ATM locations, it is determined by 3 classifications or clusters; the classification in this study is not strategic, strategic, and very strategic. In the calculation of the research, it is expected to find classification results that are by the weight of each criterion that has been determined to be a non-strategic classification so that this classification becomes new research. Strategic classification obtains comparable data from each measure in the study. Strategic classification is a pretty good classification in the placement of ATM locations. The strategic classification requires supporting factors to maintain business performance and service to customer transactions, in placing ATM locations in a very strategic classification, obtaining good data on each research criteria. Very strategic classification can also influence any research and process of establishing new ATM locations to increase business opinion and optimize transaction services for ATM users in conducting transactions. This research will develop the calculation of K-Means into web-based software.

#### RESULT

The following are the results obtained from research conducted on clustering ATM data at BNI ATM Location Placement Using the K-Means Clustering Method Case Study PT. Bank Negara Indonesia (Persero) Tbk. Denpasar Regional Office.

#### Data Used

The data used is data taken from January to June 2021. The data is grouped by 6 clustering criteria, namely ATMs Usage (K01), which is the average daily transaction, ATMs FBI (K02), which is the average monthly income of ATMs, and ATMs SLA (K03), which is the percentage of service ATMs, ATMs distance (K05) which is the distance between ATMs in meters, competitor ATMs (K05) which is the number of competitor ATMs, and Business Distance (K06) which is the distance between ATMs and the business centre in meters. There are 121 ATMs data shown in table 1, and the normalization of the ATM data is in table 2 as follows.

					Table 1		
				A	ATMs Data		
		K01	K02	K03	K04	K05	K06
No.	ATM ID	Usage	FBI	SLA	ATMs Distances	ATMs Number	<b>Business Distances</b>
		(number)	(IDR)	(%)	(meters)	(number)	(meters)
1	R10JB	6112	2488862	100	5413	1	1
2	R12CC	3930	1853614	100	5413	1	1
3	R11E0	3559	94837	100	200	10	15
4	RA007	3523	867495	100	200	10	15
5	R04KD	3937	2069631	100	494	3	100
6	R06DH	2636	1974103	100	1819	11	200
7	R11G0	2244	2335416	100	1469	1	300
8	R11F1	2348	1382795	100	8375	3	800
9	R11F0	2862	1520573	100	4807	5	500
10	R12BB	2247	1525987	100	7497	2	2,5
112	N02EK	1488	242902	100	1051	2	10
113	N02PK	1360	926348	100	427	3	10
114	N02QR	3357	1547556	100	87	4	10
115	N03AA	1968	875998	100	420	10	10
116	N03AC	4092	2446810	99	2542	5	5
117	N03DD	740	401685	100	1366	6	10
118	N03ED	4979	2623176	100	1176	6	5

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Volume 4, Number 2, July 2022 https://doi.org/10.47709/cnahpc.v4i2.1580 **Submitted** : June 27, 2022 **Accepted** : July 13, 2022 **Published** : July 23, 2022

No.	ATM ID	K01 Usage	K02 FBI	K03 SLA	K04 ATMs Distances	K05 ATMs Number	K06 Business Distances
		(number)	(IDR)	(%)	(meters)	(number)	(meters)
119	N03WW	5936	3154838	100	1176	8	200
120	N03WZ	732	398373	100	1153	6	1
121	N90RJ	5325	1938772	100	87	8	10
M	in Value	47	35002	98	76	0	1
Ma	ax Value	11235	7006315	100	22241	15	6000

Normalization of research data using the Linear Scaling Method, which aims to determine the effectiveness of the criteria in determining the predetermined classification. The test results to choose the ranking on the research criteria that affect the type of ATM placement. The results of the two tests on the user criteria, income criteria, performance criteria, and distance criteria between similar ATM locations obtain the results that the greater the value of k, the more stable the ranking results. In addition to the k factor, the criteria that influence the ranking are the criteria for many competing bank ATMs and the criteria for the distance between ATMs and business centres. Calculations for standards with positive categories are calculated in the following way.

$R10JB(K01)^* = \frac{(6112-47)}{(11235-47)} = 0,5421;$	$R10JB(K02)^* = \frac{(2488862 - 35002)}{(7006315 - 35002)} = 0,3520$
$R10JB(K03)^* = \frac{(100-98)}{(00-98)} = 1,0000;$	$R10JB(K04)^* = \frac{(5413-76)}{(22241-76)} = 0,5421$
$R10JB(K05)^* = \frac{(1-0)}{(15-0)} = 0,0667;$	$R10JB(K06)^* = \frac{(1-1)}{(6000-1)} = 0,0000$

					Table 2		
				Norm	alized ATMs Data		
No	ATM ID	K01	K02	K03	K04	K05	K06
INU.		Usage	FBI	SLA	ATMs Distances	ATMs Number	<b>Business Distances</b>
1	R10JB	0,5421	0,3520	1,0000	0,2408	0,0667	0,0000
2	R12CC	0,3471	0,2609	1,0000	0,2408	0,0667	0,0000
3	R11E0	0,3139	0,0086	1,0000	0,0056	0,6667	0,0023
4	RA007	0,3107	0,1194	1,0000	0,0056	0,6667	0,0023
5	R04KD	0,3477	0,2919	1,0000	0,0189	0,2000	0,0165
6	R06DH	0,2314	0,2782	1,0000	0,0786	0,7333	0,0332
7	R11G0	0,1964	0,3300	1,0000	0,0628	0,0667	0,0498
8	R11F1	0,2057	0,1933	1,0000	0,3744	0,2000	0,1332
9	R11F0	0,2516	0,2131	1,0000	0,2134	0,3333	0,0832
10	R12BB	0,1966	0,2139	1,0000	0,3348	0,1333	0,0003
112	N02EK	0,1288	0,0298	1,0000	0,0440	0,1333	0,0015
113	N02PK	0,1174	0,1279	1,0000	0,0158	0,2000	0,0015
114	N02QR	0,2959	0,2170	1,0000	0,0005	0,2667	0,0015
115	N03AA	0,1717	0,1206	1,0000	0,0155	0,6667	0,0015
116	N03AC	0,3615	0,3460	0,5000	0,1113	0,3333	0,0007
117	N03DD	0,0619	0,0526	1,0000	0,0582	0,4000	0,0015
118	N03ED	0,4408	0,3713	1,0000	0,0496	0,4000	0,0007
119	N03WW	0,5264	0,4475	1,0000	0,0496	0,5333	0,0332

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Volume 4, Number 2, July 2022
https://doi.org/10.47709/cnahpc.v4i2.1580

**Submitted** : June 27, 2022 **Accepted** : July 13, 2022 **Published** : July 23, 2022

No	No. ATM ID	K01	K02	K03	K04	K05	K06
INO.		Usage	FBI	SLA	ATMs Distances	ATMs Number	<b>Business Distances</b>
120	N03WZ	0,0612	0,0521	1,0000	0,0486	0,4000	0,0000
121	N90RJ	0,4718	0,2731	1,0000	0,0005	0,5333	0,0015

In this study, K-Means calculations have been implemented into a Web-based application. The following is a screenshot of the implementation results on the software shown in Figure 3 in the form of a dashboard view, Figure 4 in the form of a criteria view, Figure 5 in the form of an alternative view, Figure 6 in the form of a classification view, Figure 7 in the form of a Weighted Classification View, Figure 8 in the form of a K-Means clustering calculation. And Figure 9 is a K-Means clustering result. All phrases used in the web-based application implementation are in Indonesian.

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### Data Mining Metode K-Means

K-means merupakan salah satu algoritma clustering. Tujuan algoritma ini yaitu untuk membagi data menjadi beberapa kelompok. Algoritma ini menerima masukan berupa data tanpa label kelas. Hal ini berbeda dengan supervised learning yang menerima masukan berupa vektor (x<sub>1</sub>, y<sub>1</sub>), (x<sub>2</sub>, y<sub>2</sub>), ..., (x<sub>i</sub>, y<sub>i</sub>), di mana x<sub>i</sub> merupakan data dari suatu data pelatihan dan yi merupakan label kelas untuk x<sub>i</sub>.

Pada algoritma pembelajaran ini, komputer mengelompokkan sendiri data-data yang menjadi masukannya tanpa mengetahui terlebih dulu target kelasnya. Pembelajaran ini termasuk dalam unsupervised learning. Masukan yang diterima adalah data atau objek dan k buah kelompok (cluster) yang diinginkan. Algoritma ini akan mengelompokkan data atau objek ke dalam k buah kelompok tersebut. Pada setiap cluster terdapat titik pusat (centroid) yang merepresentasikan cluster tersebut.

K-means ditemukan oleh beberapa orang yaitu Lloyd (1957, 1982), Forgey (1965), Friedman and Rubin (1967), and McQueen (1967). Ide dari clustering pertama kali ditemukan oleh Lloyd pada tahun 1957, namun hal tersebut baru dipublikasi pada tahun 1982. Pada tahun 1965, Forgey juga mempublikasi teknik yang sama sehingga terkadang dikenal sebagai Lloyd-Forgy pada beberapa sumber.

Array			
(			
[1] => 5413			
[2] => 5413			
[3] -> 200			
[4] -> 200			
[5] => 4949			
[6] -> 1819			
[7] -> 14699			
[9] _> 9375			
[0] -> 4907			
[10] => 7407			
[10] => 7497			
[11] => 9800			
[12] => 2990			

#### Fig. 3 Dashboard view

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# Kriteria

Pencarian.	C Refresh	+ Tambah	
Kode	Nama Kriteria	Keterangan	Aksi
К01	Usage	Rata-rata penggunaan tiap bulan	6
К02	FBI	Rata rata pendapatan tiap lokasi ATM	6
К03	SLA	Service Level ATM	6
К04	Jarak ATM	Jarak dengan ATM sejenis	6
K05	Jumlah ATM	Jumlah ATM Bank pesaing dalam radius < 1 km	6
K06	Jarak Bisnis	Jarak dengan lokasi bisnis atau perdagangan	6

#### Fig. 4 Criteria View

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Submitted : June 27, 2022 Accepted : July 13, 2022 Published : July 23, 2022

Volume 4, Number 2, July 2022 https://doi.org/10.47709/cnahpc.v4i2.1580

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# Alternatif

Pe	ncarian		${\cal G}$ Refresh	🕂 Tambah 🔒	Import	oort					
No	Kode	Nama	Lat	Lng	Usage	FBI	SLA	Jarak ATM	Jumlah ATM	Jarak Bisnis	Aksi
1	1	R10JB	-8.318638	114.625618	6112	2488862	100	5413	1	1	Ø 1
2	2	R12CC	-8.318638	114.625618	3930	1853614	100	5413	1	1	Ø
3	3	R11E0	-8.115915	115.08793	3559	948370	100	200	10	15	Ø i
4	4	RA007	-8.115915	115.08793	3523	867495	100	200	10	15	c i
5	5	R04KD	-8.153473	115.030065	3937	2069631	100	4940	3	100	Ø 🕯
6	6	R06DH	-8.446933	115.616133	2636	1974103	100	1819	11	200	c i
7	7	R11G0	-8.275773	115.163111	2244	2335416	100	14690	1	300	6
8	8	R11F1	-8.530079	115.509991	2348	1382795	100	8375	3	800	6
9	9	R11F0	-8.487304	115.572677	2862	1520573	100	4807	5	500	Ø i

Fig. 5 Alternative View

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# Klasifikasi

Pencarian CRefresh						
No	Kode	Nama Klasifikasi	Aksi			
1	C01	Tidak Strategis	6			
2	C02	Strategis	6			
3	C03	Sangat Strategis	6			

### Fig. 6 Classification View

# Nilai Bobot Klasifikasi

Pencar	Pencarian C Refresh							
Kode	Nama Klasifikasi	Usage	FBI	SLA	Jarak ATM	Jumlah ATM	Jarak Bisnis	Aksi
C01	Tidak Strategis	4000	4000000	98	2000	4	3000	🕼 Ubah
C02	Strategis	5000	5000000	99	5000	3	2000	🕑 Ubah
C03	Sangat Strategis	11235	7006315	100	14690	1	1000	🕑 Ubah

Fig. 7 Weighted Classification View

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Volume 4, Number 2, July 2022	Accep
https://doi.org/10.47709/cnahpc.v4i2.1580	Publis

Submitted : June 27, 2022 Accepted : July 13, 2022 Published : July 23, 2022

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### Perhitungan







Fig. 9 K-Means Clustering Result

#### DISCUSSIONS

The graph of clustering results based on 121 ATMs data shows very strategic centroids of 27 locations or covering 22.31%, strategic several 77 locations or covering 63.64%, and non-strategic 17 locations or covering 14.05%. In this case, non-strategic ATM placement locations are a concern in evaluating ATM placements. Evaluation results provide output for re-evaluating strategic and suitable arrangements. ATM location data that is not strategic as 14.05% is caused because K03, K04, and K05 become criteria that affect the classification significantly. K03, which is an ATM performance, gets a low score due to some repetitive software and hardware damage that takes a long time to repair, so it will make customers reluctant to transact at ATMs. Distance from similar ATMs is very influential in business placement. The same product is placed in adjacent areas providing conditions that divide the results in that area. The order of ATM locations is not optimal. 6. The number of ATMs of competing banks has a considerable influence. Several banks are competing in placing ATMs in locations that are considered reasonable and have a market. The greater the number of competitor bank ATMs in a close radius, the greater the business competition. If the service to ATM users is interrupted, the placement of ATMs will not be strategic.

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Journal of Computer Networks, Architecture and	
High Performance Computing	Submitted : June 27, 2022
Volume 4, Number 2, July 2022	Accepted : July 13, 2022
https://doi.org/10.47709/cnahpc.v4i2.1580	<b>Published</b> : July 23, 2022

The steps taken by banks to deal with the problem of placing ATMs that are not strategically found several agreements, namely evaluating the bank's business plan in 2022 and improving supervision of machines at ATM locations. Evaluating a bank's business plan provides a solution to assess non-strategic ATM placements. Submissions for areas that do not have good business are then submitted to the relocation or relocation process. Supervise and monitor machines located at ATM locations to ensure they can serve customers well. The ATM is damaged, so it is informed to get treatment by a machine technician immediately. ATM managers relocate ATM locations that are not classified as strategic. Managers consider business risks and high operational costs compared to revenues and optimize ATM services to customers. The following are the relocation stages that have taken place in the first half of 2022 at non-strategic ATM locations. This research is also applied in implementing web-based software tested by white box and black box testing with good results. Table 3 shows the results of alternative classifications based on K-Means on very strategic centroids of 27 locations or covering 22.31%, strategic several 77 locations or covering 63.64%, and non-strategic 17 locations or covering 14.05%.

Table 3 ATMs Data K-Means Clustering Result

No.	ATM ID	Centroid	No.	ATM ID	Centroid	No	ATM ID	Centroid
1	R10JB	very strategic	42	SA095	non-strategic	83	S118T	non-strategic
2	R12CC	strategic	43	S118V	strategic	84	S118U	strategic
3	R11E0	strategic	44	SA021	very strategic	85	S118W	strategic
4	RA007	strategic	45	SA030	strategic	86	S12DD	strategic
5	R04KD	strategic	46	S04JV	very strategic	87	NA034	non-strategic
6	R06DH	strategic	47	SA110	very strategic	88	NA031	strategic
7	R11G0	strategic	48	S03WR	strategic	89	NA065	very strategic
8	R11F1	strategic	49	S02LJ	strategic	90	N04JZ	strategic
9	R11F0	strategic	50	S04JH	very strategic	91	NA078	very strategic
10	R12BB	strategic	51	S04JM	strategic	92	N11C1	strategic
11	RA003	strategic	52	S04JN	strategic	93	NA038	strategic
12	RA001	very strategic	53	S12CC	strategic	94	N119L	strategic
13	RA002	strategic	54	SA084	very strategic	95	N12DD	strategic
14	RA008	strategic	55	S12RR	strategic	96	N12BY	strategic
15	RA006	very strategic	56	S12UU	very strategic	97	NA025	strategic
16	RA010	very strategic	57	S12NN	very strategic	98	NA035	strategic
17	RA014	non-strategic	58	SA072	strategic	99	N12CP	strategic
18	RA012	non-strategic	59	S03RQ	strategic	100	NA046	strategic
19	RA013	strategic	60	N10IY	non-strategic	101	NA053	strategic
20	RA015	very strategic	61	S03XL	strategic	102	A02HJ	strategic
21	RA016	very strategic	62	S02QQ	non-strategic	103	A03DC	strategic
22	RA018	very strategic	63	S02RR	strategic	104	A03SB	strategic
23	RA017	very strategic	64	S02RT	strategic	105	A03SC	strategic
24	RA023	strategic	65	S03CJ	strategic	106	A04JP	non-strategic
25	RA020	strategic	66	S03CK	strategic	107	A04JT	strategic
26	RA021	strategic	67	S03FB	non-strategic	108	A04JU	strategic
27	RA022	very strategic	68	S03WT	strategic	109	N06IB	strategic
28	RA024	strategic	69	S03XM	very strategic	110	N02AS	non-strategic
29	RA025	strategic	70	S04JL	very strategic	111	N02DE	non-strategic
30	S04JI	strategic	71	S10IC	non-strategic	112	N02EK	strategic

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Volume 4, Number 2, July 2022 https://doi.org/10.47709/cnahpc.v4i2.1580 **Submitted** : June 27, 2022 **Accepted** : July 13, 2022 **Published** : July 23, 2022

No.	ATM ID	Centroid	No.	ATM ID	Centroid	No	ATM ID	Centroid
31	SA012	non-strategic	72	S10ID	very strategic	113	N02PK	strategic
32	SA014	strategic	73	N10IX	strategic	114	N02QR	strategic
33	SA016	non-strategic	74	N10IZ	very strategic	115	N03AA	strategic
34	SA013	very strategic	75	S08KF	strategic	116	N03AC	non-strategic
35	SA003	very strategic	76	S118Q	strategic	117	N03DD	strategic
36	SA028	very strategic	77	S118P	strategic	118	N03ED	strategic
37	SA048	strategic	78	S118R	non-strategic	119	N03WW	very strategic
38	SA053	strategic	79	S119X	strategic	120	N03WZ	strategic
39	SA019	very strategic	80	S118Z	strategic	121	N90RJ	strategic
40	SA057	strategic	81	S118O	non-strategic			
41	SA075	strategic	82	S118X	strategic			

#### CONCLUSION

This one succeeded in evaluating the placement of BNI ATM locations using the K-Means Clustering Method Case Study of PT. Bank Negara Indonesia (Persero) Tbk. Denpasar Regional Office well and overall expectations. Based on the 121 ATMs data used for the K-Means calculation, 3 centroids were determined, namely very strategic, strategic, and not strategic, each of which yielded values of 22.31%, 63.64%, and 14.05%. Although the location of ATMs classified as non-strategic criteria is relatively small, this can be optimized by several strategic steps that stakeholders can take within the company, such as evaluating the bank's business plan in 2022 and improving the supervision of machines at ATM locations. This research is also applied in implementing web-based software tested by white box and black box testing with good results. For further similar research, it can improve the quality of the test so that it can provide more accurate results.

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