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Enhancing Banking Services through Data-Driven ATM Placement Strategies: A Case Study of PT Bank Rakyat Indonesia

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Abstract

This research optimizes the placement strategy for new Automated Teller Machines (ATMs) at PT Bank Rakyat Indonesia (BRI). The study employs a data-driven methodology that integrates data preparation, clustering techniques, and coefficient calculations to identify the most suitable ATM locations. This approach goes beyond static models by incorporating customer behavior and transaction data.

The methodology utilizes a two-pronged approach. The first phase assesses the potential of various districts for ATM placement, considering factors such as demographics, transaction patterns, and competitor presence. K-means clustering is then employed to prioritize districts with the highest potential for benefiting from additional ATMs. The second phase involves calculating coefficients by analyzing correlations between existing ATM distribution and district potential scores. This analysis provides data-driven recommendations for the optimal number of new ATMs in each district.

By leveraging robust methodological framework, this research offers valuable insights for strategic decision-making and resource allocation. The proposed approach can enhance banking service accessibility across diverse regions, improve customer satisfaction, and contribute to the optimization of BRI's ATM network.

A. Introduction

The strategic placement of Automated Teller Machines (ATMs) serves as a crucial factor in enhancing accessibility to banking services and optimizing customer convenience. This research project focuses on the optimization of ATM placement strategies for PT Bank Rakyat Indonesia (BRI), a prominent and progressive bank. The expansion of ATM networks involves intricate decisions shaped by factors such as geographic distribution, demographics, and transaction patterns. To address these challenges, this study proposes a comprehensive methodology that merges data analysis, clustering techniques, and coefficient calculations, enabling informed recommendations for the placement of new ATMs.

As one of Indonesia's largest banks, BRI is committed to elevating its services to accommodate a diverse customer base across various districts. The strategic placement of ATMs in key locations can significantly impact customer satisfaction, operational efficiency, and overall business success. However, conventional approaches to ATM placement often rely on static models, lacking adaptability to evolving customer behaviors and banking trends.

Several studies have explored various aspects relevant to optimizing ATM placement strategies. ATM placement and its impact have been extensively researched, with studies showing a clear link between strategic placement and financial success. For example, research indicates that well-placed ATMs can generate significantly higher revenue compared to poorly located ones [1]. A comprehensive study conducted by [2] delves into the factors influencing ATM placement, emphasizing the importance of market-centric considerations.

Data-driven approaches and customer segmentation play a crucial role in optimizing ATM placement. Machine learning tools, such as K-means clustering and Support Vector Machines (SVM), have been employed to predict customer churn and develop effective retention strategies [3]. Similarly, K-means clustering enables customer segmentation for targeted marketing campaigns and product development tailored to specific customer groups [4]. Big data analytics, combined with clustering algorithms, are also utilized for real-time cash management of ATMs, optimizing cash replenishment and maintenance [5]. The superiority of advanced machine learning models over traditional methods in credit scoring is highlighted in a literature survey [6]. Furthermore, the effectiveness of customer segmentation using K-means clustering is supported by its application in credit risk assessment and financial fraud detection [7][8].

Beyond ATMs, optimization techniques are applicable in various financial and operational domains. Multi-criteria decision-making (MCDM) approaches help identify suitable ATM locations practically [9]. Combining fuzzy logic and optimization algorithms optimizes cash management in ATMs, ensuring adequate cash availability while minimizing costs [10]. Optimization techniques also extend to cash replenishment and vehicle routing for ATMs, balancing customer demand fulfillment with cost minimization [11]. These techniques have broader applicability, as evidenced by their use in residential solid waste collection route optimization [12].

The field of finance continuously evolves, exploring topics such as the impact of financial inclusion on market stability [13] and the influence of environmental, social, and governance (ESG) factors on bank performance [14].

While existing studies have contributed valuable insights into ATM placement strategies, there remains a need for a more dynamic and data-driven approach that incorporates real-time customer behavior and transaction data. Additionally, the integration of clustering techniques and coefficient calculations can enhance the decision-making process and lead to more informed ATM placement decisions. Beyond performance, various parameters, including competitor ATM presence and determining the appropriate number of ATMs, are considered. This comprehensive framework integrates performance data and potential district parameters to strategically deploy ATMs for optimal customer access.

The findings of this study are expected to contribute significantly to the banking and business optimization literature by offering a practical and data-driven approach to ATM placement. The proposed methodology can be adopted by BRI and other financial institutions to enhance their ATM networks, and, ultimately, improve customer satisfaction.

B. Methodology and Analysis

In this section, we will discuss the approaches we have used to achieve our objective. Our research focuses on an exploratory approach to determine the best locations for new ATMs. We have received a request from the Business Operation Division at PT Bank Rakyat Indonesia (BRI) to identify optimal ATM placements. However, due to limitations, we have not had extensive discussions with the Business Operation Division team to fully understand their requirements. Nonetheless, we have pursued various approaches designed to fulfill this goal.

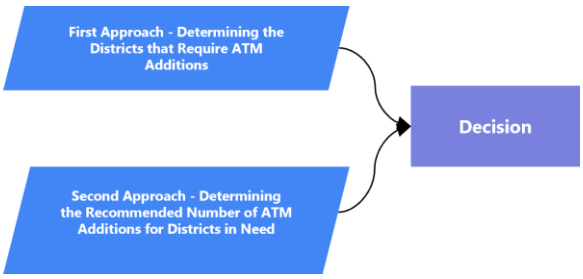

Figure 1. Block Diagram of The Strategy

Our research employs two distinct approaches, as illustrated in Figure 1. The first approach involves scoring each district based on various parameters, such as District Potential, BRI ATM Performance, and Count of ATMs from BRI and other bank. Through data preparation, scaling, and scoring, we identify districts in dire need of ATM additions, with clustering helping to prioritize those with the highest urgency. The second approach determines coefficients to represent the District Potential Score, which aids in recommending the appropriate number of ATM additions for districts requiring them. Together, these two approaches hopefully will empower decision-makers at PT Bank Rakyat Indonesia (BRI) to make informed and strategic choices in expanding their ATM network, ultimately enhancing banking services and customer experiences across different regions.

The research was conducted during the month of June of 2023, with data collection taking place in May of 2023 to ensure the utmost comprehensiveness of the dataset. By capturing the most up-to-date information available at the time, we aim to provide a robust foundation for our analysis and insights. This temporal alignment allows us to consider the latest trends and dynamics that may influence the outcomes of our research, enhancing its relevance and applicability.

1. First Approach - Determining the Districts that Require ATM Additions

In pursuit of our objective, we have employed a well-structured approach as illustrated in Figure 2 - the Block Diagram of the First Approach. Our methodology encompasses several key stages, each designed to ensure a comprehensive evaluation of districts and their suitability for new ATM placements.

Figure 2. Block Diagram of the First Approach

The first step involves data preparation, where we compile and gather a wide range of parameters, drawing from both internal sources and external data on ATM locations from other banks. These parameters are essential in comprehensively assessing the potential for new ATM installations in each district. To bolster our analysis, we have also incorporated insights from previous analytical projects undertaken within our division, which have been validated by the company.

To facilitate a fair and standardized evaluation, we then implement a rigorous scaling method. This process transforms the raw parameter values into a unified 1-10 scale, allowing for consistent comparisons and comprehensive analysis. Subsequently, we devise a scoring method that amalgamates the various sub-parameters into a single, holistic score for each district. This scoring mechanism is pivotal in ranking the districts based on their overall potential, BRI ATM performance, and the number of existing ATMs, providing crucial insights for our decision-making process regarding ATM additions.

To further refine our analysis, we employ K-means clustering, a powerful algorithm that groups districts based on their final scores. This step enables us to identify distinct clusters of districts with similar characteristics, aiding us in making well-informed recommendations for ATM placements.

Our multi-faceted approach, encompassing data preparation, scaling, scoring, and clustering, forms a robust analytical framework. It allows us to confidently identify the districts most in need of ATM additions, taking into account their specific characteristics and needs. By following this well-structured methodology, we can strategically allocate resources and maximize the impact of ATM expansions, ultimately enhancing banking services in the targeted areas.

1.1. Data Preparation

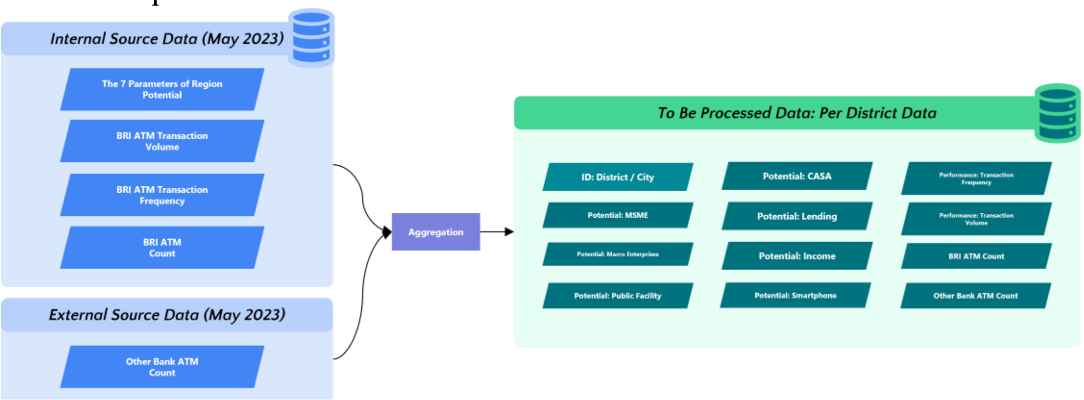

Figure 3. Data Processing Block Diagram

In Figure 3 - the Data Processing Block Diagram, we illustrate the process of data handling and integration by aggregation to ensure the robustness and reliability of our research. The data utilized in this study comprises two distinct components. Firstly, a significant portion of the data is derived from previous projects conducted within PT Bank Rakyat Indonesia (BRI) and has undergone rigorous validation, ensuring its reliability and validity. This internal data provides valuable insights into various parameters and contributes to the overall robustness of our analysis.

In addition to the internal data, we have also incorporated external data sources to augment our research. Specifically, we have gathered information regarding the number of ATMs from other banks, along with their corresponding coordinates. By incorporating this external data, we expand the scope of our analysis and gain a more comprehensive understanding of the ATM landscape in the target regions. This combination of internal and external data sources enables us to capture a holistic view of the ATM distribution and better inform our recommendations.

By integrating these diverse datasets, we aim to enhance the reliability our research, enabling us to make well-informed conclusions and provide valuable insights for effective decision-making within the context of ATM placement strategies.

The initial data processing phase entails aggregating the data at the district level, thereby reducing the total number of districts from 7,266 to 3,323. This aggregation is achieved through an inner join operation, which filters the data to include only those districts that have BRI ATMs. As a result, we obtain three sets of parameters that serve as the foundation for our analysis:

1. District Potential Parameters:
    a. Business Activity Score 1: Micro, Small, and Medium Enterprises (MSMEs)

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   b. Business Activity Score 2: Macro Enterprises
   c. Business Activity Score 3: Public Facilities
   d. Smartphone Penetration Score
   e. CASA (Current Account, Savings Account) Ratio Score
   f. Loan Score
   g. District Income Score
2. District BRI ATM Performance Paremters:
   a. Cash Withdrawal Transaction Volume
   b. Cash Withdrawal Transaction Frequenc
3. Dsitrict Number of BRI and Other Bank ATMs:
   a. Number of BRI ATMs
   b. Number of ATMs from Other Bank

Table 1. Each Parameters

No.	***Sub-Parameter***
1	Cash Withdrawal Volume
2	Cash Withdrawal Frequency
3	Business Activity 1
4	Business Activity 2
5	Business Activity 3
6	Smartphone Penetration Score
7	CASA Score
8	Loan Score
9	District Income Score
10	Number of BRI ATM
11	Number of Other Bank ATM

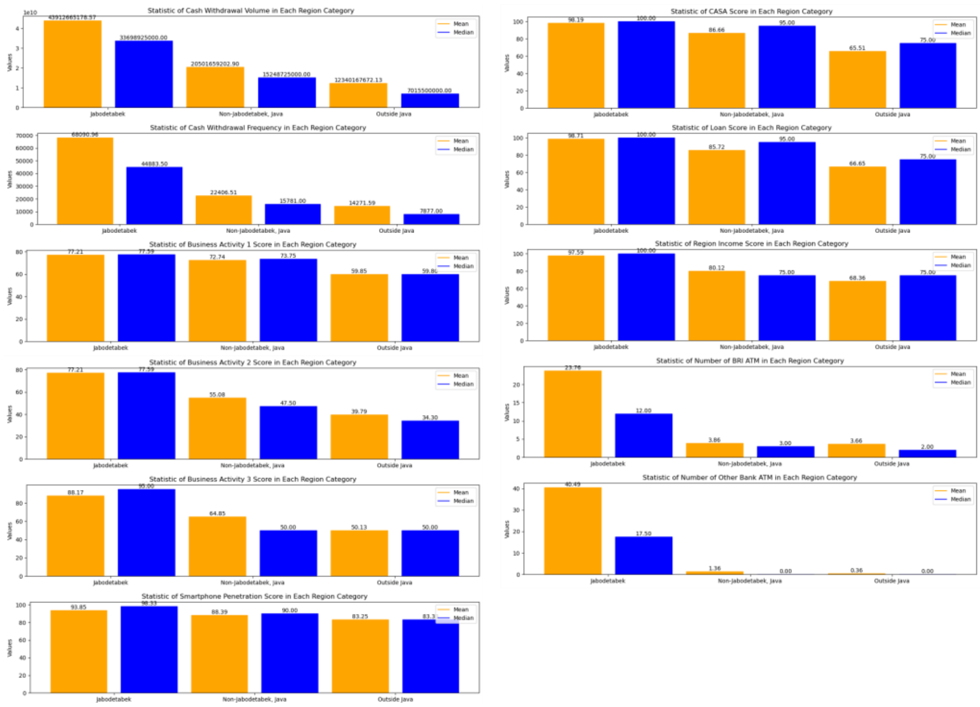

Figure 4. Each Parameter Statistics in each region types

Table 1 - Each Parameter and Figure 4 - Each Parameter Statistics present a comprehensive overview of the data's characteristics for each parameter. Each parameter exhibits a distinct range of values, showcasing variability across the districts under analysis. To ensure a comprehensive and in-depth evaluation, we have classified the data based on PT Bank Rakyat Indonesia's (BRI) standards, dividing it into urban and rural categories. Furthermore, the data is stratified into regional classifications: Jabodetabek (encompassing areas in close proximity to the capital city), Non-Jabodetabek regions within Java (representing districts on the same island as the capital city), and districts located outside of Java.

By adopting this separation by region approach and delving into the nuances of each parameter's conditions, we can uncover valuable insights and make informed decisions regarding ATM placement strategies tailored to the unique characteristics of each district.

Within each parameter, we provide detailed explanations of their respective conditions, shedding light on the specific factors influencing their values. This comprehensive analysis facilitates a better understanding of the underlying dynamics and assists in identifying patterns and trends across the districts.

1.2. Scaling and Scoring

To achieve a standardized evaluation of each district, we employ a scaling technique using the following formula:

$$\text{Scaled Value} = \left(\frac{\text{Original Value} - \text{Min}_{\text{Original}}}{\text{Max}_{\text{Original}} - \text{Min}_{\text{Original}}}\right) \times (\text{Max}_{\text{Scaled}} - \text{Min}_{\text{Scaled}}) + \text{Min}_{\text{Scaled}} \quad (1)$$

This formula scales the original values to a standardized range, enabling fair comparisons and uniform contributions to the evaluation process.

Table 2. Scaled Parameter Statistics

No.	*Sub-Parameter*	*Mean*	*Std*	*Median*
1	Cash Withdrawal Volume	1.903908252	0.972798663	1.609544692
2	Cash Withdrawal Frequency	1.417458319	0.532257194	1.250406055
3	Business Activity 1	7.017190102	1.41856363	7.212990937
4	Business Activity 2	5.3659142	2.170773372	4.945317221
5	Business Activity 3	6.244729864	2.211835268	5.5
6	Smartphone Penetration Score	8.739393437	0.937285005	8.95
7	CASA Score	7.875812065	1.834662523	7.75
8	Loan Score	7.890429234	1.796190156	7.75
9	District Income Score	7.734115015	1.789440627	7.75
10	Number of BRI ATM	1.361540556	0.586135412	1.160714286
11	Number of Other Bank ATM	1.093564396	0.526658251	1

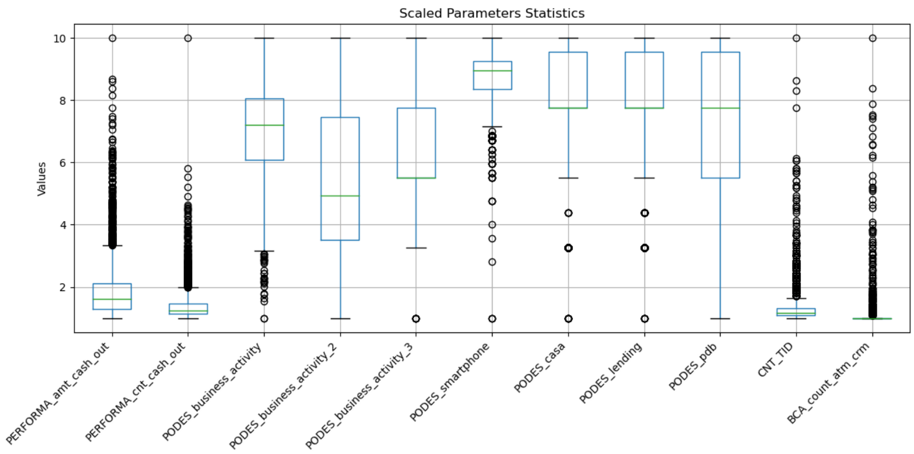

Figure 5. Scaled Parameter Statistics

The box plot presented in and the statistics value in the Table 2 represents the distributions of parameters and its visual in the Figure 6, illustrating the medians and ranges for each. When considering these parameters collectively, a clear polarization emerges between performance-related metrics, such as the count of BRI and other bank ATMs, and parameters related to district potential. The distribution of performance-related metrics skews towards lower values, indicating areas where improvements and optimizations are needed. Conversely, parameters associated with district potential exhibit a wider distribution and relatively higher values, pointing to areas with greater potential for ATM installations and banking services. This comprehensive analysis allows us to better understand the specific needs and opportunities in each district, guiding the strategic placement of ATMs and optimizing banking services.

In the subsequent phase, after scaling all the parameters, the data undergoes the scoring process. In this process, the individual sub-parameters are aggregated into three main parameters: district potential, BRI ATM performance, and ATM count. The scoring procedure involves summing the sub-parameters within each parameter group to derive three distinct scores: the District Potential Score, the BRI ATM Performance Score, and the ATM Count Score. The weights assigned to these sub-parameters cannot be predetermined without consultation and discussion with the Business Operation Division. Since the division currently lacks a specific method for determining new ATM locations, we have opted for an unbiased approach by equalizing the weights of each sub-parameter. This ensures fairness and eliminates potential bias in the scoring process.

Scoring plays a crucial role in evaluating and ranking the different aspects of the analysis. In this process, the individual sub-parameters are aggregated into three main parameters: district potential, BRI ATM performance, and ATM count. The scoring procedure involves utilizing the following formula:

$$\text{Final Score} = \left(\frac{\text{Regional Potential Score}}{\text{BRI ATM Performance Score}}\right) \times \left(\frac{1}{\text{ATM Count Score}}\right) \tag{2}$$

This formula calculates the Final Score, which represents the level of need for ATM additions in each district. It is derived by dividing the Regional Potential Score

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by the BRI ATM Performance Score, and then multiplying the result by the reciprocal of the ATM Count Score. Through this scoring formula, we can effectively evaluate and rank the districts based on their level of need, enabling us to prioritize ATM additions and allocate resources more efficiently.

By employing this scoring methodology, we are able to assess the overall performance and potential of each district in a comprehensive manner. The scores serve as a reliable indicator of the relative needs and priorities for ATM additions, allowing for informed decision-making and resource allocation.

Based on the scoring formula, we have generated a simulation table as shown in Table 3 that ranks the districts according to their level of need for ATM additions. The highest score in the simulation indicates districts with higher potential and performance compared to the existing number of ATMs, highlighting the need for additional installations. On the other hand, districts in the middle range demonstrate a balanced ratio between the number of ATMs and their potential and performance, with variations determined by the available data. Conversely, districts with high or moderate potential and performance that have low score has a ~~numerous ATMs~~numerous ATM.

Table 3. Score Usage Simulation Table

Regional Potential Score	*BRI ATM Performance Score*	*ATM Count Score*	*Final Score*
100 (High)	10 (Low)	10 (Low)	1
100 (High)	100 (High)	10 (Low)	0.1
100 (High)	10 (Low)	100 (High)	0.1
10 (Low)	10 (Low)	10 (Low)	0.1
100 (High)	100 (High)	100 (High)	0.01
10 (Low)	100 (High)	10 (Low)	0.01
10 (Low)	10 (Low)	100 (High)	0.01
10 (Low)	100 (High)	100 (High)	0.001

Considering the scores generated through our analysis, we can identify districts where the existing ATM infrastructure may be insufficient to meet the demands of the local population or support the economic activities in the area. These districts with higher scores indicate a higher priority for ATM additions to better serve the community and optimize banking services.

This comprehensive analysis enables us to prioritize and allocate resources effectively, ensuring that ATM additions are targeted where they can have the greatest impact. By understanding the relationship between the number of ATMs, district potential, and performance, we can make informed decisions and recommendations to enhance the ATM network and meet the specific needs of each district.

Overall, this methodological approach combines scaling and scoring techniques to provide a robust framework for assessing the need for ATM additions in different districts. It aligns with the goal of achieving an impartial and transparent evaluation, allowing for informed decision-making regarding the allocation of resources and addressing the urgent requirements of the communities in need.

Table 4. Regional Potential Score Statistics

Region Type	*Count*	*Mean*	*Std*	*Median*
Jabodetabek	112	63.8812979	3.095164007	65.1006798
Non-Jabodetabek, Java	1380	55.0999328	7.94146599	54.3791541
Outside Java	1525	46.0818938	11.09977974	45.9030212

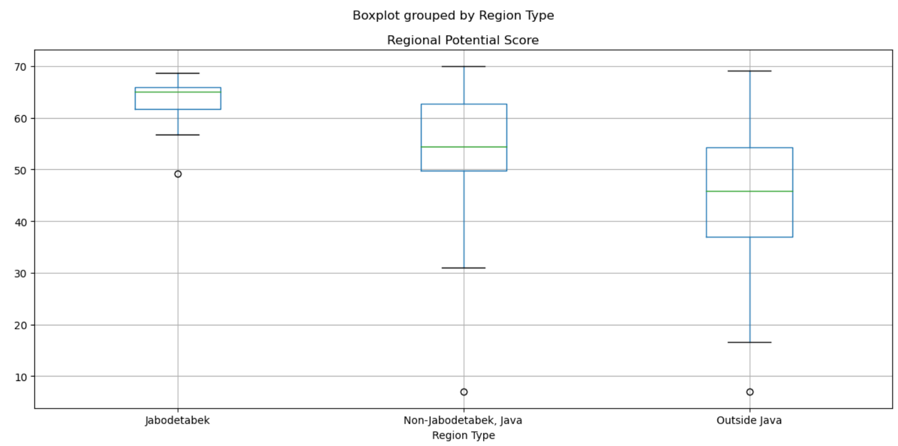

Figure 6. Regional Potential Score Statistics Plot

Table 5. BRI ATM Performance Score Statistics

Region Type	*Count*	*Mean*	*Std*	*Median*
Jabodetabek	112	5.72359529	3.116375632	4.63852777
Non-Jabodetabek, Java	1380	3.54249695	1.418295928	3.13001976
Outside Java	1525	2.94483572	1.118224162	2.54111566

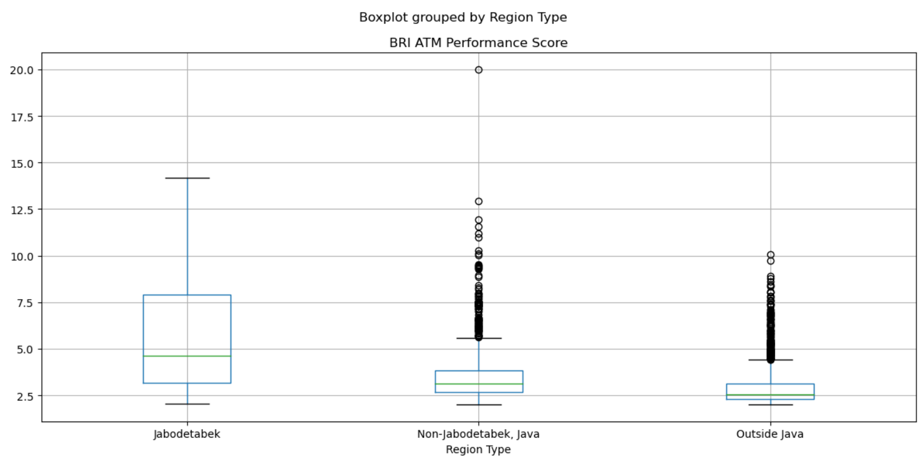

Figure 7. BRI ATM Performance Score Statistics Plot

Table 6. Number of ATM Score Statistics

Region Type	*Count*	*Mean*	*Std*	*Median*
Jabodetabek	112	5.55072954	3.806139802	3.57275579
Non-Jabodetabek, Java	1380	2.3656528	0.503314484	2.24107143
Outside Java	1525	2.30870103	0.420222096	2.16071429

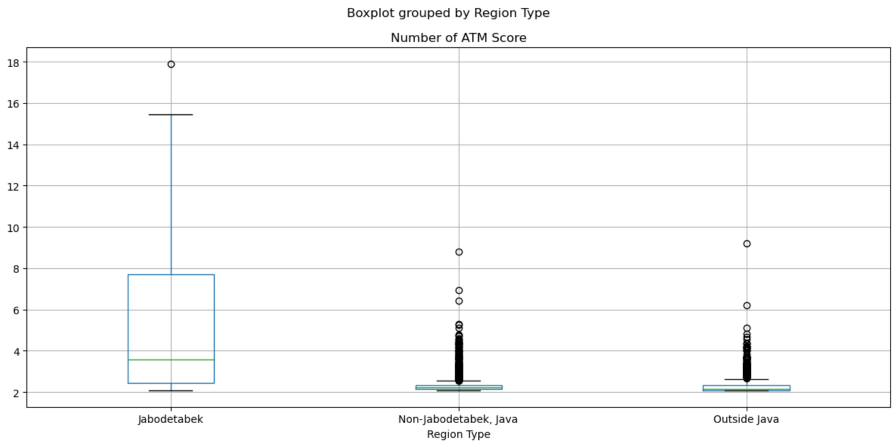

Figure 8. Number of ATM Score Statistics Plot

Table 7. Final Score

Region Type	*Count*	*Mean*	*Std*	*Median*
Jabodetabek	112	4.72111395	3.946084497	3.74468041
Non-Jabodetabek, Java	1380	7.4280777	2.262504876	7.64153176
Outside Java	1525	7.38727705	2.199846314	7.46348824

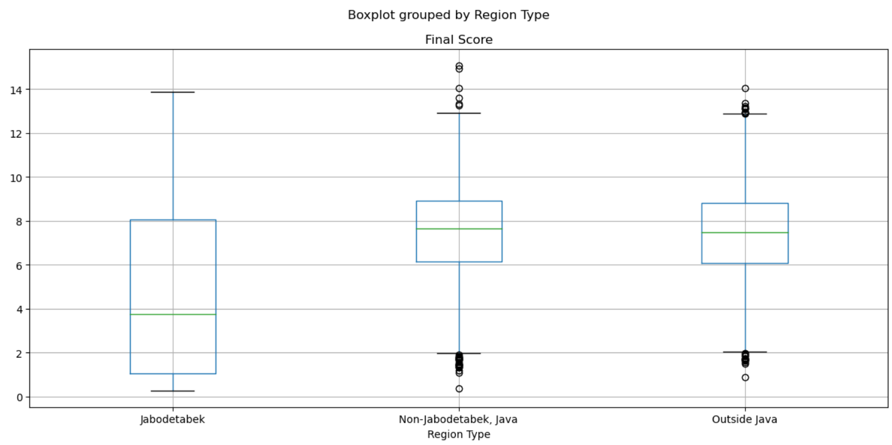

Figure 9. Final Score Plot

By considering the final scores, we can effectively prioritize resource allocation and deployment of new ATMs to districts in need. This data-driven approach ensures that limited resources are allocated to districts with the highest potential impact, optimizing the distribution of ATMs and maximizing the accessibility of banking services across various districts.

To provide future guidance and facilitate discussions with the Business Operation Division regarding the weighting and prioritization of sub-parameters or parameters, we have conducted an analysis of the significance of each sub-parameter on the final score as shown in Table 8. This analysis enables us to better understand the impact of each sub-parameter and make informed decisions regarding their relative importance in determining the final score.

Table 8. Significance: Correlation to each Corresponding Parameter Group

Parameter	*Regional Potential Score*	*BRI ATM Performance Score*	*ATM Count Score*	*Final Score*
Cash Withdrawal Volume	0.55	***0.99***	0.69	-0.75
Cash Withdrawal Frequency	0.49	***0.98***	0.79	-0.73
Business Activity 1	***0.85***	0.52	0.27	-0.14
Business Activity 2	***0.94***	0.54	0.34	-0.1
Business Activity 3	***0.93***	0.52	0.34	-0.09
Smartphone Penetration Score	***0.72***	0.45	0.26	-0.11
CASA Score	***0.87***	0.42	0.25	0.01
Loan Score	***0.89***	0.43	0.26	0.02
District Income Score	***0.9***	0.41	0.28	0.05
Number of BRI ATM	0.38	0.84	***0.95***	-0.64
Number of Other Bank ATM	0.23	0.53	***0.93***	-0.38

By examining the significance of each sub-parameter, we can identify which factors have a stronger influence on the overall assessment of district needs for ATM additions. This analysis helps in identifying key drivers that contribute significantly to the final score and allows us to prioritize these factors when considering the allocation of resources and decision-making processes.

By conducting such an analysis, we aim to ensure that the final scoring process is robust, transparent, and aligned with the specific objectives and requirements of the Business Operation Division. This analysis serves as a valuable tool for future discussions, enabling us to tailor the weighting and prioritization of sub-parameters or parameters based on the specific needs and preferences of the division.

Ultimately, this analysis strengthens the validity and reliability of our research findings, enhancing the accuracy and effectiveness of the decision-making process when determining the allocation of resources and the implementation of ATM additions in districts across Indonesia.

1.3. Clustering

Figure 10. Clustering Block Diagram

Following the scoring of all districts, as shown in Figure 10, the score data is utilized for clustering purposes. The rationale behind clustering stems from the understanding that the Business Operation Division may not be able to add ATMs to all districts across Indonesia. To address this possibility, clustering techniques are applied to group districts into clusters based on their scored data.

The primary objective of clustering is to prioritize districts that require ATM additions by identifying clusters with the highest mean final score. By clustering districts based on their characteristics and similarities, we can identify groups of districts that share similar needs and requirements for ATM installations. This proactive approach allows us to identify the districts that are in the greatest need of ATM additions, ensuring that resources are allocated strategically to maximize their impact.

Clustering serves as an effective strategy to optimize resource allocation and decision-making processes. It helps us identify clusters of districts with similar characteristics and requirements, enabling us to target specific groups of districts that have the highest need for ATM additions. By focusing our efforts on these high-priority clusters, we can ensure that our initiatives align with the specific needs and priorities of the districts, maximizing the overall effectiveness of ATM deployment and improving banking services in the targeted areas.

Through this proactive clustering approach, we can streamline the decision-making process, effectively prioritize districts, and optimize resource allocation. This ultimately leads to more efficient and impactful ATM additions, ensuring that the districts with the greatest need for improved banking services are prioritized and served accordingly.

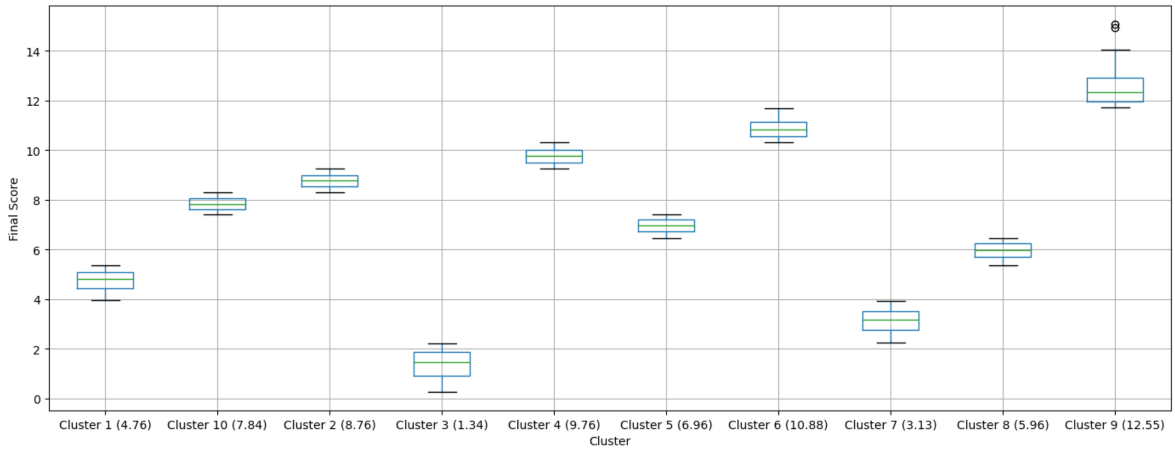

Figure 11. The Spread of the Clusters

Plotting the clusters as box plots in Figure 11 provides a comprehensive overview of each cluster's central tendency, specifically the mean final score. This visualization allows us to identify the cluster with the highest mean final score, indicating the districts in the most urgent need of ATM additions.

By examining the box plots, we gain insights into the distribution and variability of the final scores within each cluster. This analysis helps us understand the diversity of needs and characteristics among the districts within each cluster.

Identifying the cluster with the highest mean final score is crucial as it highlights the districts that require immediate attention and resources for ATM additions. By prioritizing this cluster, we can ensure that the districts with the greatest need are adequately served and their banking services are enhanced.

In summary, the cluster with the highest mean final score, indicating the districts in most urgent need of ATM additions. This visualization aids in prioritizing resource allocation and decision-making processes, ensuring that the districts with the greatest need receive the necessary attention and support for improved banking services.

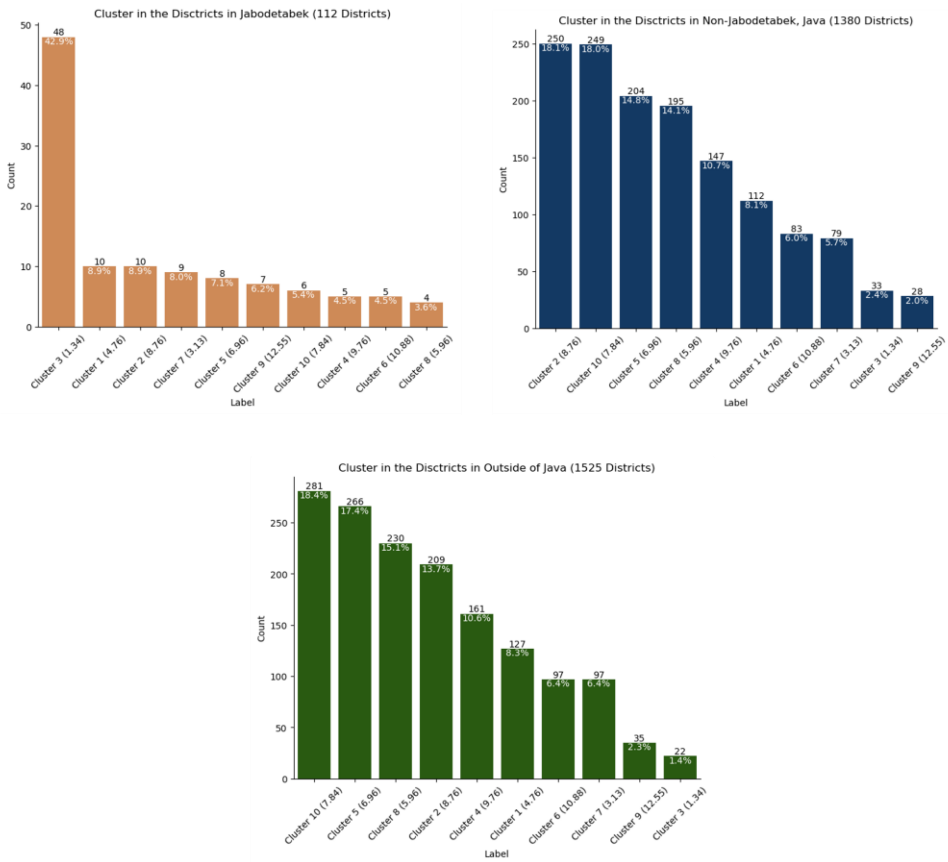

Figure 12. Clusters in Each of the Region Types (upper left: Jabodetabek; upper right: Non-Jabodetabek, Java; bottom: Outside Java)

The plot in Figure 12 visualizes the clusters based on frequency counts per region, specifically categorizing them into Jabodetabek, Non-Jabodetabek within Java, and regions outside Java. By examining the plot, we can observe that the cluster indicating the highest need for ATM additions consists of 70 districts distributed across Non-Java, Java (Non-Jabodetabek), and Jabodetabek regions.

This information is significant as it highlights the areas where ATM additions are most urgently required. The presence of a considerable number of districts in this cluster across different regions suggests a widespread need for improved banking services and access to ATMs. This finding emphasizes the importance of prioritizing resources and initiatives in these specific regions to address the identified needs and meet the demands of the population.

Analyzing the distribution of districts across different regions allows us to understand the geographical scope and impact of the cluster with the highest need for ATM additions. It indicates the potential for enhancing banking services and improving financial accessibility in various areas, ultimately benefiting the communities residing in those regions.

By identifying this cluster and its geographical distribution, we can devise targeted strategies and allocate resources effectively to address the ATM needs and improve banking services in these specific regions. This knowledge enables us to focus our efforts and interventions in a manner that maximizes the impact and ensures the equitable provision of essential financial services.

2. Second Approach - Determining the Recommended Number of ATM Additions for Districts in Need

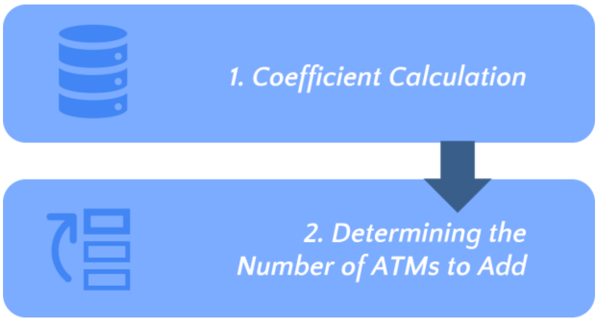

Figure 13. Block Diagram of the Second Approach

The steps as shown in Figure 13, first the coefficients are calculated to represent the district potential score as a single value. This calculation involves analyzing the correlation between the number of ATMs and the Podes score in districts that already have a sufficient number of ATMs. The purpose of this analysis is to determine the relationship between the existing ATM count and the district potential.

Table 9. The Correlation Between Final Score and the Regional Potential Score

	Final Score	*Regional Potential Score*
Final Score	1	0.7512415
Regional Potential Score	0.7512415	1

Based on the correlation analysis as shown in Table 9, coefficients are derived to establish a quantitative relationship between the number of ATMs and the desired Podes score. These coefficients serve as multipliers or weights to indicate the appropriate number of ATM additions required in districts that demonstrate a need for them.

By applying these coefficients to the districts with identified ATM needs, we can recommend the optimal number of ATM additions for each district based on their specific Podes score. This approach ensures that the ATM additions are aligned with the district's potential and the desired level of service provision.

The utilization of coefficients in determining the required number of ATM additions enhances the precision and effectiveness of the recommendations. It allows for a more tailored and data-driven approach in addressing the ATM needs of different districts, ultimately optimizing the allocation of resources and ensuring efficient expansion of ATM services where they are most needed.

2.1. Coefficient Calculation

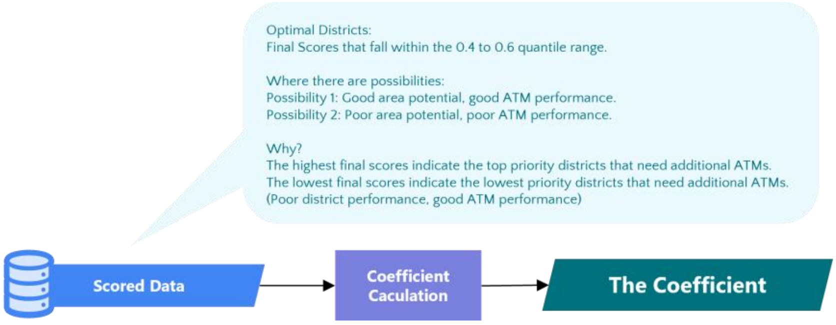

Figure 14. Block Diagram of Coefficient Calculation

How the coefficient ~~are~~is calculated are shown in the block diagram as shown in Figure 13. The coefficients are calculated to serve as multipliers or weights. This calculation focuses on districts that already have a sufficient number of ATMs, as determined by their final scores falling within the quantile range of 0.4 to 0.6. Within this range, two potential scenarios are considered to determine the appropriate number of ATM additions:

1. High Score: Indicates districts with good potential and a low number of ATMs.
2. Moderate Score: Indicates districts where the potential and the number of ATMs ~~are~~is balanced.
3. Low Score: Indicates districts with higher potential compared to the number of ATMs.

By considering these three scenarios, we can effectively prioritize districts for ATM additions based on their specific characteristics and needs. The highest final scores indicate districts with the highest priority for ATM additions, as they possess both high potential and good ATM performance. On the other hand, the lowest final scores indicate districts with lower priority due to their lower potential, even though their existing ATMs exhibit good performance. This approach allows for a comprehensive assessment of district needs, considering both district potential and ATM performance, to ensure that ATM additions are strategically implemented where they are most warranted. By differentiating between districts based on their characteristics, resources can be allocated efficiently to maximize the impact of ATM expansions and enhance overall banking services in the targeted areas.

To calculate the coefficient that represents a balanced score for district potential and BRI ATM count, we utilize the following formula:

$$\text{coefficient} = \frac{\text{count ATM BRI}}{\text{mean score potential}} \tag{3}$$

This approach allows for a comprehensive assessment of district needs, considering both district potential and ATM performance, to ensure that ATM additions are strategically implemented where they are most warranted. By differentiating between districts based on their characteristics, resources can be allocated efficiently to maximize the impact of ATM expansions and enhance overall banking services in the targeted areas.

2.2. Determining the Number of ATM Additions

The calculated coefficients serve as multipliers or weights to determine the recommended number of ATM additions in districts requiring them within the identified clusters. By applying these coefficients to the districts in need, we can estimate the appropriate number of ATM additions based on their potential scores. This approach ensures that the allocation of ATM resources aligns with the district's potential and performance, allowing for strategic and targeted expansions to meet the banking needs of each district.

C. Result and Discussion

1. Approach 1

Below is the table summarizing the raw values of each sub-parameter before scaling and scoring, along with their corresponding scores:

Table 10. First Approach Result

No	*District / City (Unique)*	*Region Type*	*Regional Potential Score*	*BRI ATM Performance Score*	*ATM Count Score*	*Score*	*Cluster*
1	AJUNG / JEMBER	Non-Jabodetabek, Java	63.17	2.59	02.08	11.73	9
2	BATANG CENAKU / INDRAGIRI HULU	Outside Java	60.43	2.37	2.16	11.78	9
3	KUMPEH ULU / MUARO JAMBI	Outside Java	56.66	2.31	02.08	11.79	9
4	SUKAMAKMUR / BOGOR	Jabodetabek	59.76	2.43	02.08	11.84	9
...	...	...	...	...	...	...	...
67	CIBEBER / CIANJUR	Non-Jabodetabek, Java	64.27	2.20	02.08	14.04	9
68	BANGKO PUSAKO / ROKAN HILIR	Outside Java	61.59	02.03	2.16	14.05	9
69	BLIMBINGSARI / BANYUWANGI	Non-Jabodetabek, Java	63.39	02.04	02.08	14.95	9
70	CISURUPAN / GARUT	Non-Jabodetabek, Java	63.81	02.03	02.08	15.07	9

Table 10 provides an overview of the original values for each sub-parameter before undergoing the scaling and scoring process. The raw values represent the specific measurements or data points associated with each sub-parameter. The corresponding scores indicate the transformed values obtained through the scaling and scoring procedures, reflecting the relative importance or significance of each sub-parameter in the final analysis.

By examining this table, we can gain insights into the range and distribution of the raw values, as well as the resulting scores. These scores will be further utilized in subsequent analyses, such as clustering or determining the final scores for each district.

2. Approach 2

Table 11. Second Approach Result

No	*District / City (Unique)*	*Regional Potential Score*	*Current Number of ATM*	*Recommended ATM Number*	*Number of ATM Addition*
1	AJUNG / JEMBER	63.17	1	3	**2**
2	BATANG CENAKU / INDRAGIRI HULU	60.43	2	3	**1**
3	KUMPEH ULU / MUARO JAMBI	56.66	1	2	**1**
4	SUKAMAKMUR / BOGOR	59.76	1	3	**2**
...	...				
67	CIBEBER / CIANJUR	64.27	1	3	**2**
68	BANGKO PUSAKO / ROKAN HILIR	61.59	2	3	**1**
69	BLIMBINGSARI / BANYUWANGI	63.39	1	3	**2**
70	CISURUPAN / GARUT	63.81	1	3	**2**

The result in table 11 provides a comprehensive summary of the raw values of each sub-parameter before scaling and scoring, along with the corresponding scores. It also includes information on the optimal number of ATMs in each district and the recommended number of ATM additions based on our methodology. The optimal number of ATMs represents the ideal number for each district, while the recommended ATM additions indicate the number of ATMs that should be added based on our methodology, taking into account the existing number of ATMs in each district.

By referring to this summary, decision-makers can easily assess the district-level data and identify the districts with higher scores, indicating a greater need for ATM additions. This information allows for a targeted allocation of resources, ensuring that ATM installations are strategically implemented in areas where they are most needed. By focusing on districts with higher scores and a larger recommended number of ATM additions, the banking services in these areas can be enhanced, providing improved accessibility and a better customer experience.

D. Conclusion

In conclusion, this study serves a comprehensive methodology has been presented for identifying optimal sites to establish new ATMs for PT Bank Rakyat Indonesia (BRI). By conducting a seamless integration of data preparation, scaling, scoring, clustering, and coefficient calculations, a robust framework has been established, enabling efficient and informed choices for expanding the ATM network. The initial approach successfully pinpoints districts that would benefit from additional ATMs by evaluating their potential and clustering districts with similar characteristics. The subsequent approach tailors recommendations for new ATM placements based on the scores of district potential.

Through this research, the crucial role of data-driven decision-making in resource allocation optimization and enhancement of banking services has been highlighted. The methodologies not only facilitate the identification of high-priority districts for focused ATM additions but also ensure alignment with district-specific requirements and potential. This comprehensive approach contributes to the efficiency of ATM expansion, ultimately resulting in improved customer experiences and accessibility to financial services.

As the banking sector continues to evolve, this research offers pertinent insights for effectively addressing the dynamic challenges of ATM placements. By combining rigorous analytical techniques with practical applications, this study sets the stage for strategic expansion of the ATM network. This benefits both PT Bank Rakyat Indonesia (BRI) and its customers by providing heightened banking services and improved accessibility.

E. References

[1] Faculty of Cyberphysical Systems, Department of Physics of High Technologies, Oguz Han Engineering and Technology University of Turkmenistan, Ashgabat, Turkmenistan, S. Nokerov, G. Akmyradov, Faculty of Cyberphysical Systems, Department of Cyberphysical Systems, Oguz Han Engineering and Technology University of Turkmenistan, Ashgabat, Turkmenistan, D. Badulescu, and Faculty of Economic Sciences, Department of Economics and Business, University of Oradea, Oradea, Romania, "ANALYSIS OF THE OPTIMAL LOCATION OF BANK AUTOMATED TELLER MACHINES (ATMS) IN TURKMENISTAN," *OJBE*, pp. 103–113, Mar. 2023, doi: 10.47535/1991ojbe177.

[2] A. Rastogi, Y. Sharma, S. Mukherji, R. K. Kaliyar, and V. K. Baghel, "Predictive Analysis of Optimal Automated Teller Machine Site Selection Using Machine Learning and Deep Learning: A Comprehensive Study on Variables, Challenges, and Opportunities," in *2023 International Conference on Electrical, Electronics, Communication and Computers (ELEXCOM)*, Roorkee, India: IEEE, Aug. 2023, pp. 1–6. doi: 10.1109/ELEXCOM58812.2023.10370336.

[3] H. Dang Tran, N. Le, and V.-H. Nguyen, "Customer Churn Prediction in the Banking Sector Using Machine Learning-Based Classification Models," *IJIKM*, vol. 18, pp. 087–105, 2023, doi: 10.28945/5086.

[4] E. Y. L. Nandapala and K. P. N. Jayasena, "The practical approach in Customers segmentation by using the K-Means Algorithm," in *2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS)*, RUPNAGAR, India: IEEE, Nov. 2020, pp. 344–349. doi: 10.1109/ICIIS51140.2020.9342639.

[5] M. Almansoor and Y. Harrath, "Big Data Analytics, Greedy Approach, and Clustering Algorithms for Real-Time Cash Management of Automated Teller Machines," in *2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, Zallaq, Bahrain: IEEE, Sep. 2021, pp. 631–637. doi: 10.1109/3ICT53449.2021.9581890.

[6] X. Dastile, T. Celik, and M. Potsane, “Statistical and machine learning models in credit scoring: A systematic literature survey,” *Applied Soft Computing*, vol. 91, p. 106263, Jun. 2020, doi: 10.1016/j.asoc.2020.106263.
[7] C. Dang, X. Chen, S. Yu, R. Chen, and Y. Yang, “Credit ratings of Chinese households using factor scores and K-means clustering method,” *International Review of Economics & Finance*, vol. 78, pp. 309–320, Mar. 2022, doi: 10.1016/j.iref.2021.12.014.
[8] G. Sahoo and S. S. Sahoo, “Accounting Fraud Detection Using K-Means Clustering Technique,” in *Machine Learning and Information Processing*, vol. 1311, D. Swain, P. K. Pattnaik, and T. Athawale, Eds., in Advances in Intelligent Systems and Computing, vol. 1311. , Singapore: Springer Singapore, 2021, pp. 171–180. doi: 10.1007/978-981-33-4859-2_17.
[9] N. Goker and M. Dursun, “MCDM Approach for Locating Automatic Teller Machines: An Application in Turkish Banking Sector,” *WSEAS TRANSACTIONS ON COMPUTERS*, vol. 20, pp. 10–16, Apr. 2021, doi: 10.37394/23205.2021.20.2.
[10] A. Tunç and S. Taşdemir, “Fuzzy Based Weighted, Arithmetic Optimization Algorithm (AOA) for Cash Management Optimization on Automatic Teller Machines (ATM),” in *Intelligent and Fuzzy Systems*, vol. 504, C. Kahraman, A. C. Tolga, S. Cevik Onar, S. Cebi, B. Oztaysi, and I. U. Sari, Eds., in Lecture Notes in Networks and Systems, vol. 504. , Cham: Springer International Publishing, 2022, pp. 287–294. doi: 10.1007/978-3-031-09173-5_36.
[11] D. Orhan and M. Erol Genevois, “Cash Replenishment and Vehicle Routing Improvement for Automated Teller Machines,” in *Intelligent and Fuzzy Systems*, vol. 758, C. Kahraman, I. U. Sari, B. Oztaysi, S. Cebi, S. Cevik Onar, and A. Ç. Tolga, Eds., in Lecture Notes in Networks and Systems, vol. 758. , Cham: Springer Nature Switzerland, 2023, pp. 721–729. doi: 10.1007/978-3-031-39774-5_80.
[12] K. N. Mpeta, E. Munapo, and M. R. Ngwato, “Route Optimization for Residential Solid Waste Collection: Mmabatho Case Study,” in *Intelligent Computing and Optimization*, vol. 1072, P. Vasant, I. Zelinka, and G.-W. Weber, Eds., in Advances in Intelligent Systems and Computing, vol. 1072. , Cham: Springer International Publishing, 2020, pp. 506–520. doi: 10.1007/978-3-030-33585-4_50.
[13] D. H. Vo, N. T. Nguyen, and L. Thi-Hong Van, “Financial inclusion and stability in the Asian region using bank-level data,” *Borsa Istanbul Review*, vol. 21, no. 1, pp. 36–43, Mar. 2021, doi: 10.1016/j.bir.2020.06.003.
[14] R. El Khoury, N. Nasrallah, and B. Alareeni, “ESG and financial performance of banks in the MENAT region: concavity–convexity patterns,” *Journal of Sustainable Finance & Investment*, vol. 13, no. 1, pp. 406–430, Jan. 2023, doi: 10.1080/20430795.2021.1929807.