

Market Potential Analysis Based on Population and Land Area using K-Means Clustering and MCDM Approaches

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Submitted: 19/05/2025; Accepted: 30/06/2025; Published: 30/06/2025

Abstract—In an increasingly competitive global market, accurately identifying untapped market potential in small to medium-sized regions, often overlooked by traditional single-indicator analyses, presents a significant challenge for strategic decision-making. This study addresses this by proposing a hybrid analytical framework integrating K-Means Clustering with Multi-Criteria Decision-Making (MCDM) methods, utilizing population size and land area as core indicators. The primary objective is to develop a robust market potential analysis model capable of systematically classifying regions and providing actionable insights for resource optimization and market expansion. The methodology involves determining the optimal number of clusters using the elbow method ($k=3$, with a silhouette score of 0.8862), followed by K-Means clustering to segment Asian countries into distinct groups. Subsequently, three MCDM methods SAW, WP, and WASPAS are applied to rank countries within the most relevant cluster (low population and area) under various weighting scenarios. The results consistently demonstrate Turkey's top ranking across all MCDM methods, highlighting its robust market potential regardless of weight variations. Crucially, a very strong agreement in rankings between the MCDM methods was observed, evidenced by Spearman's correlation coefficients consistently above 0.98, with the highest correlation between SAW and WASPAS (0.998379 for [0.3, 0.7] weights). This high correlation confirms the reliability and consistency of the model, concluding that SAW and WASPAS are highly suitable for this analysis, and identifying Turkey as the leading country in market potential among 50 Asian nations based on the criteria studied.

Keywords: K-Means; MCDM; SAW; WP; WASPAS; Elbow Method; The Spearman Rank Correlation

1. INTRODUCTION

In the era of globalization and increasing market competition, identifying market potential has become a crucial element in strategic decision-making for both businesses and regional development planners. Two fundamental indicators often used in this analysis are population size and land area. However, regions with small to medium populations and land sizes are frequently overlooked, despite the fact that they may hold untapped market potential. These areas can offer opportunities due to localized demands, resource efficiency, or emerging infrastructure factors that are not always reflected in raw demographic or geographic statistics.

The main challenge lies in systematically identifying and evaluating these regions, as the data involved is often multidimensional and varied. Traditional methods that rely solely on single indicators, such as population count, tend to produce biased or incomplete assessments of market viability. Thus, a more comprehensive analytical framework is needed one that accounts for multiple criteria and uncovers meaningful patterns within the data.

To address this issue, this study proposes a hybrid approach that integrates the K-Means Clustering algorithm with a Multi-Criteria Decision-Making (MCDM) method. K-Means is employed to group regions with similar characteristics, while MCDM is utilized to assign weights to each criterion, such as population and land area, based on their relative importance [10][11]. This combination enables a more balanced and informed classification of market potential, particularly in areas with moderate demographic and geographic scales.

When faced with complex decisions that involve multiple factors, Multi-Criteria Decision Making (MCDM) proves to be invaluable. Whether making personal decisions or crafting business strategies, we often need to choose the best option from several alternatives, each with its own set of advantages and disadvantages. This challenge lies at the heart of decision-making, and MCDM assists by assessing various criteria to identify the most optimal solution. MCDM techniques are widely applied across different industries, including finance and engineering [1]–[4]. This study will delve into several MCDM approaches, including the SAW, WP, WASPAS methods. These three approaches will be compared to determine the best solution in the context of ideal Market Potential Analysis Based on Population and Land Area. MCDM is used to make decisions based on the final outcomes or preferences derived from the chosen method. For instance, The SAW method calculates the sum of the weighted performance values of each alternative, while the WP method multiplies these values and The WASPAS method merges the SAW and WP techniques to improve accuracy [5]–[9].

Previous research conducted by Teuku Rizky Noviandy, et al. in 2024, this study explores Indonesia's diverse regions by analyzing the interplay between economic growth and environmental quality. Using K-means clustering on 2022 data for Air Quality Index (AQI), electricity consumption, and Gross Regional Domestic Product (GRDP), the provinces were grouped into three clusters, each reflecting distinct economic and environmental characteristics [10].

A study by Setiawansyah and Very Hendra Saputra in 2023 successfully applied the SAW method, combined with PIPRECIA-S weighting, to elect the chairman of a school organization. The results showed that Jamaludin was elected as chairman with the highest score of 1.821, followed by Bustomi with 1.763, and Budiman with 1.698. The

majority of respondents (98%) agreed or strongly agreed with the election results, indicating the method's effectiveness and acceptance in the decision-making process [11].

In a separate study conducted by Dinda Fransiska in 2020, the WP (Weighted Product) method was found to be effective in determining the best alternative for choosing an e-commerce platform. The decision-making process involved calculating criterion values, adjusting weights, computing the S and V vector values, and identifying the highest value to rank the alternatives. The analysis highlighted that customer trust and product quality were prioritized over other factors such as ease of use, promotions, and appearance. The e-commerce platform with the highest value was selected as the recommended choice [12].

In 2023, research by Fahrul Mahdi and colleagues focused on the challenges companies face when selecting permanent employees from contract staff, often due to a lack of objectivity in the process. Their study demonstrated that utilizing the WASPAS and ROC methods, which take into account multiple relevant criteria, enhanced the decision-making process. This approach resulted in a more accurate and optimal selection, with contract employee A2 being chosen as the best candidate for permanent employment, based on a utility value of 0.982, calculated using these methods [13].

Previous research has demonstrated the usefulness of combining clustering techniques with MCDM in areas such as customer segmentation, regional planning, and site selection. However, limited studies have applied this integrated approach specifically for market potential analysis using population and land area as the core indicators especially in regions with small to medium characteristics. This research aims to fill that gap.

The objective of this study is to develop a market potential analysis model that leverages the strengths of both K-Means Clustering and MCDM methods to classify regions based on population size and land area. The resulting model is expected to support more accurate and actionable insights for decision-makers, business strategists, and policymakers seeking to optimize resource allocation and market expansion strategies.

2. RESEARCH METHODOLOGY

The research process consists of a sequence of actions undertaken by researchers with the aim of generating new insights or knowledge. An overview of these steps is presented in the illustration shown in Figure 1.

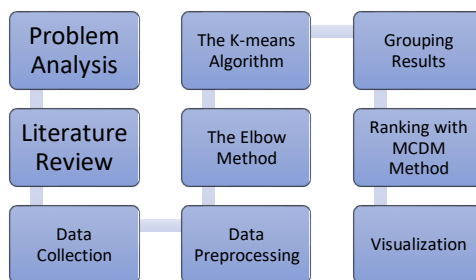


Figure 1. Research Stages

Based on the illustration in Figure 1, the stages described above cover several important processes, ranging from problem analysis to visualisation, which will be presented in a report that is the result of observations, research, or specific activities, either in written or verbal form.

2.1 Problem Analysis

This study begins by identifying a key issue: how to classify countries within the Asian continent based on their market potential, considering variables such as population size and land area. Smaller and mid-sized nations are often underrepresented in market evaluations despite their possible strategic value. Therefore, a structured and data-driven framework is essential to provide fair and objective segmentation.

2.2 Literature Review

At this stage, existing studies involving clustering algorithms, especially K-Means, and multi-criteria decision-making (MCDM) methods such as SAW, WP, WASPAS are examined. The aim is to explore methodological approaches that combine unsupervised learning with decision analysis, while also identifying research gaps in applying these techniques to regional market assessments.

2.3. Data Collection

The data used in this research is obtained from the "Worldwide Countries Dataset" available on Kaggle, which provides comprehensive information for countries globally, including attributes like population and area. For this research, the dataset is filtered to include only countries located in Asia. From various regions, this study focuses only on Asia, so the number of data samples used in this study is 50 countries. The following are details of countries based on population and area.



Tabel 1. Sampel Data

Name	Capital	Population	Area
Taiwan	Taipei	23503349	36193
Indonesia	Jakarta	273523621	1904569
Laos	Vientiane	7275556	236800
China	Beijing	1402112000	9706961
Yemen	Sana'a	29825968	527968
...
Israel	Jerusalem	9216900	20770

2.4 The Elbow Method

To find the most suitable number of clusters, the Elbow Method is used. This technique calculates the within-cluster sum of squares (WCSS) across different values of k to identify the point where adding more clusters does not significantly reduce variance. The elbow point is then selected as the optimal cluster count for the K-Means model. In addition, the study also calculated the silhouette score value of the number of clusters considered optimal in order to see the quality of the clustering results used in conjunction with the elbow method to help determine the optimal number of clusters.

2.5 The K-Means Algorithm

K-Means is a widely used clustering technique in data analysis that partitions data points into a predefined number of clusters based on their attribute similarities. The primary objective of the K-Means algorithm is to identify central points referred to as centroids for each group, such that data instances exhibiting similar characteristics are grouped together. The process begins by specifying the number of clusters (k) and initializing the centroids, typically chosen at random. Subsequently, the algorithm computes the distance from each data point to all centroids and assigns each point to the nearest one. Once all data points are assigned, the centroids are recalculated as the mean of all points within each cluster. This procedure is repeated iteratively reassigning data points and updating centroids until the cluster assignments stabilize or a predefined convergence criterion is met [32][33][34][35][36][37]. Once the optimal number of clusters is determined, the K-Means algorithm is employed to classify the Asian countries into clusters based on their demographic and geographical features. Each country is assigned to a cluster based on similarity metrics, which helps in forming distinct market groupings.

The implementation of K-Means typically follows these steps: first, determine the number of clusters; next, during the initial iteration, centroids are established using randomly selected data points. Following this, the distance between each data point and the current centroids is calculated usually using Euclidean distance, as shown in Equation 1 below to assign each point to the nearest cluster

$$d_{Euclidean}(X, Y) = \sqrt{\sum_{i=1}^n (X_i - Y_i)^2} \tag{1}$$

The notation $d(x, y)$ represents the distance between a data point x and the centroid of cluster y . Here, X_i refers to the i -th instance in the n -th attribute, and i also denotes the j -th instance within the same attribute space. Data points that are closer in distance to a particular cluster center are assigned to that cluster, whereas those with larger distances are allocated to separate clusters. Proceed to the next iteration by updating the centroid positions, which are calculated based on the data points assigned to the nearest group. The computation is detailed in Equation 2 below.

$$K_i = \frac{1}{M} \sum_{j=1}^M X_j \tag{2}$$

The procedure is repeated starting from the initial step and continues through each iteration. As long as the centroids of the clusters continue to shift, the algorithm will proceed. However, once the centroids remain fixed and no longer move, the iteration process is terminated.

2.6 Grouping Results

The resulting clusters are evaluated to understand the unique profiles of each group. For instance, one group may consist of high-population, low-area nations, while another includes large-area countries with smaller populations. These groupings provide a strategic foundation for analyzing regional market characteristics. The grouping results that will be used in the next process are countries that are grouped into smaller populations and areas than other clusters.

2.7 Ranking with MCDM Method

To refine the analysis, MCDM methods[14]–[19] are applied to rank the countries within each cluster. This involves assigning weights to each indicator based on their relevance to market potential. Using techniques such as SAW, WP and WASPAS, each country receives a composite score, enabling prioritized market rankings.



2.7.1 SAW Method

One of the techniques commonly applied in Decision Support Systems is the Simple Additive Weighting (SAW) method. This approach calculates the total weighted score for each alternative by summing its performance values across all criteria. To begin, a decision matrix (X) is constructed, which contains the evaluation scores of all alternatives against the defined criteria. This matrix is then normalized depending on the type of attribute either benefit or cost. For benefit-type attributes, normalization is typically performed using a specific formula (e.g., Equation 3), while cost-type attributes are normalized using another method (e.g., Equation 4), resulting in a normalized matrix (R). In the final phase, the preference value for each alternative is computed by applying weighted summation to the normalized scores, as outlined in Equation 5[20].

$$R_{ij} = \frac{x_{ij}}{\text{Max}_{x_{ij}}} \tag{3}$$

$$R_{ij} = \frac{\text{Min}_{x_{ij}}}{x_{ij}} \tag{4}$$

$$V_i = \sum_{j=1}^n R_{ij} * W_j \tag{5}$$

The description of the SAW method formula includes X_{ij} is the data converted into matrix form, R_{ij} is the normalised performance level, V_i is the ranking of each preference value and W_j is the weight or importance of each criterion[21].

2.7.2 WP Method

The Weighted Product (WP) method is commonly utilized in multi-criteria decision-making (MCDM) situations, mainly due to its efficient computational approach. The fundamental principle behind this technique involves adjusting each alternative’s performance on a specific criterion by applying a weight, which represents the criterion's relative importance. This adjustment is carried out through multiplication, effectively capturing the contribution of each criterion to the overall evaluation[22][23][24].

The application of the WP method follows a well-defined series of steps. First, each criterion is assigned a numerical weight (denoted as “w”), indicating its relevance in the decision-making process. If these weights have already been determined by the decision-maker or through earlier analysis, this step may be skipped. However, if the weights need to be computed, they can be derived using a specific mathematical formula, often referred to as “equation 6,” which quantifies the relative significance of each criterion, ensuring the weights align with the decision-maker's priorities.

$$W_j = \frac{w_j}{\sum w_j} \tag{6}$$

$$S_i = \prod_{j=1}^n X_{ij}^{W_j} \tag{7}$$

$$V_i = \frac{S_i}{\sum S_i} \tag{8}$$

After assigning weights, the next step is to calculate the preference vector value ‘S’ obtained by multiplying the criterion value of each alternative by its respective weight (equation 7). This “S” value is then normalised to produce the preference vector ‘V’, which allows direct comparison of alternatives (equation 8). The ‘S’ vector reflects the initial evaluation of each alternative, while the ‘V’ vector provides the final ranking adjusted for the weights and nature of the criteria, with higher values indicating stronger preferences.

2.7.3 WASPAS Method

The WASPAS (Weighted Aggregated Sum Product Assessment) method is a technique in MCDM used to evaluate alternatives based on various relevant criteria. This approach combines weighted judgment and aggregated product summation to generate a preference or performance score for each alternative. In the WASPAS method, each criterion is assigned a weight to reflect its importance, and then a calculation is performed by multiplying the weights and values of the respective criteria, followed by summing the results. These results are used to compare and rank alternatives in the decision-making process. The WASPAS method begins by creating a decision matrix, as shown in equation 9, followed by normalization based on the type of criteria defined earlier. Normalization for benefit-type criteria is done using equation 10, while for cost-type criteria, equation 11 is applied. The final step is to calculate the preference value (Q_i) using equation 12[25][26].

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{mn1} & x_{mn2} & \dots & x_{mn} \end{bmatrix} \tag{9}$$

$$R_{ij} = \frac{x_{ij}}{\text{Max}_{x_{ij}}} \tag{10}$$

$$R_{ij} = \frac{\text{Min } x_{ij}}{x_{xij}} \tag{11}$$

$$Q_i = 0,5 \sum_{j=1}^n R_{ij} W_j + 0,5 \prod_{j=1}^n (R_{ij})^{W_j} \tag{12}$$

2.8 Visualization

Finally, visual tools are utilized to represent the outcomes clearly. This may involve mapping clusters geographically across Asia, displaying rankings using bar charts or radar plots and using scatter plots to show feature relationships and cluster positioning. These visualizations are essential for communicating findings effectively to decision-makers and stakeholders involved in market strategy or regional development planning.

3. RESULTS AND DISCUSSION

In this section, we will discuss the results of market potential analysis conducted using the K-Means Clustering approach combined with the Multicriteria Decision Making (MCDM) method. The main objective of this study is to identify and group regions based on market potential determined by two main factors, namely population size and area size. The analysis process was carried out by determining the optimal number of clusters in the study using the elbow method, supported by the silhouette score of the clusters considered optimal. The data was then divided into several clusters using the K-Means algorithm, which was further analysed using the MCDM method to determine weights and priorities based on relevant criteria.

The results obtained from clustering will provide an overview of the market characteristics in each cluster formed, as well as determine the regions with high market potential based on population composition and area size. Using the MCDM method, each region is given a weight based on the criteria mentioned earlier. This discussion will examine how the clustering results provide insights into the distribution of market potential across various regions, as well as how the integration of K-Means and MCDM can enhance the accuracy of market potential mapping. Additionally, the influence of parameters used in K-Means, such as the number of clusters and the selection of parameters like the determination of the importance weights of both criteria for MCDM, on the final analysis results will also be discussed. Figure 2 shows the results of applying the elbow method in determining the number of clusters to be used in this study.

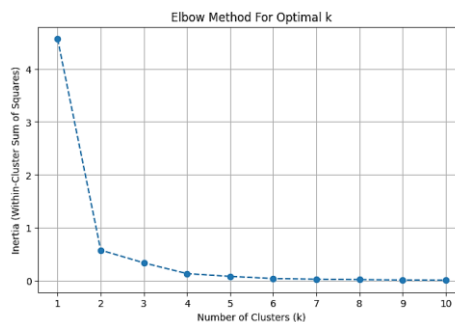


Figure 2. Elbow Method For Determining The Number Of Clusters

From the graph in Figure 2, it can be seen that the inertia value decreases sharply from k=1 to k=2, and continues to decrease gradually until k=10. However, the most significant decrease occurs up to k=3. After k=3, the decrease in inertia becomes very small and tends to flatten out. This point is called the ‘elbow point,’ which is the optimal point where adding more clusters does not provide a significant improvement in cluster quality. Therefore, based on this graph, the optimal number of clusters is k = 3. This means that dividing the data into three groups provides the best balance between model complexity and data proximity within clusters. Upon checking, the silhouette score is sufficiently high, reaching 0.8862 for three clusters. After determining the number of clusters, Figure 3 shows the results of clustering using the K-Means method with the formation of 3 clusters.

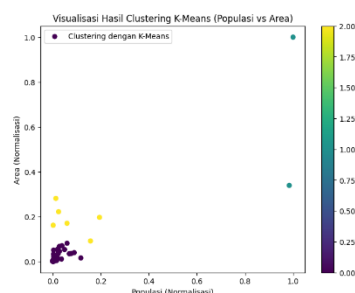


Figure 3. K-Means Method For Clustering



From the visualisation in Figure 3, it can be seen that the data is divided into three main clusters. The first cluster (marked in purple) dominates the lower part of the graph, with low population and area values. This indicates that most of the regions have relatively small populations and areas compared to other regions. The second cluster (yellow) consists of regions that are larger than the first cluster, but with populations that are still in the low to moderate range. Meanwhile, the third cluster (blue-green) consists of two extreme points, namely regions with very high populations but small areas, and regions with very large areas but low populations. These two regions can be considered outliers because they are far from the concentration of other points in the visualisation. This distribution illustrates significant variation in demographic and geographic characteristics between regions. Through this clustering, researchers will use the first cluster as more targeted regional assessment data for analysis using advanced approaches such as MCDM in strategic decision-making.

This study will use three MCDM methods in clustering data ranking, namely SAW, WP, and WASPAS. In addition to ranking, this study will also assess the performance of the three methods based on the weight of the criteria used so that the consistency of the ranking results can be seen as the level of importance changes. This study will use five criteria weighting scenarios, including 50:50, 60:40, 70:30, 30:70, and 40:60. For further clarification, the results of the ranking using the SAW method can be seen in Figure 4 below.

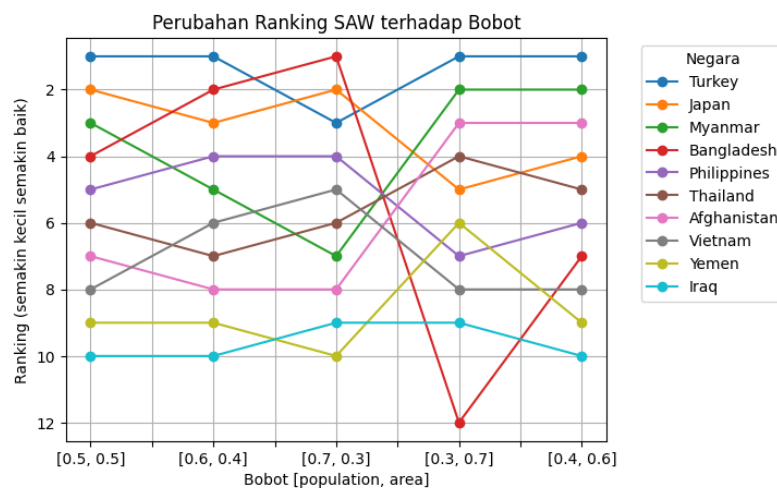


Figure 4. The Ranking Using The SAW Method

Figure 4 shows ‘Changes in SAW Rankings based on Weighting,’ which illustrates how the rankings of 10 countries change based on SAW with varying weights for two criteria: population and area. The X-axis represents the weight combinations for population and area, such as [0.5, 0.5] (population weight 0.5, area weight 0.5), up to [0.4, 0.6]. The Y-axis shows the ranking, where lower numbers indicate a better ranking.

From the graph, we can observe the fluctuations in each country's ranking. For example, Turkey (dark blue) consistently ranks at the top (1 or 2) in most weight combinations, indicating strong performance regardless of relative changes between population and area. Conversely, Bangladesh (red) shows drastic ranking changes, from 2nd to 12th, and then rising again, indicating high sensitivity to weight changes. Countries like Japan (orange) and Myanmar (green) also show ranking movements, though not as extreme as Bangladesh. Overall, this graph provides a visual representation of how each country's ranking sensitivity varies with changes in the weights of the criteria used in the SAW method. The ranking using the WP method can be seen in Figure 5 below.

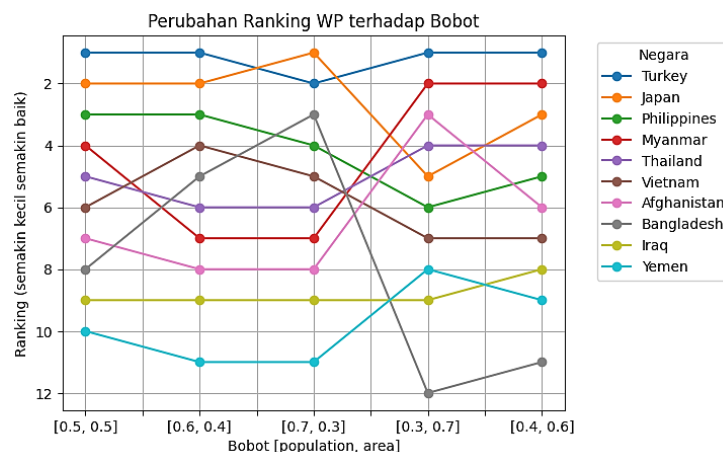


Figure 5. The Ranking Using The WP Method

Figure 5 shows ‘Changes in WP Ranking against Weight’, which is similar to the previous figure but uses the WP (Weighted Product) method to determine country rankings. As before, the X-axis shows the weight combination for population and area, starting from [0.5, 0.5] to [0.4, 0.6]. The Y-axis represents the ranking, where smaller numbers indicate a better ranking. Overall, this graph illustrates how the rankings of ten different countries shift as the relative weights between population and area change in the WP method calculation. Turkey (dark blue) appears very stable at the top of the rankings, always occupying the 1st or 2nd position, indicating high performance consistency. Japan (orange) also shows good performance, despite fluctuations, having briefly held the top ranking. Myanmar (green) and the Philippines (purple) show more dynamic ranking movements in the middle range. Afghanistan (grey) exhibits the most dramatic ranking changes, moving from a middle-range position to a very low ranking (12th) at the weight combination [0.3, 0.7], then rising again. Meanwhile, Iraq (yellow) and Yemen (light blue) tend to be in the lower rankings, although Yemen shows a slight improvement at the [0.3, 0.7] point. These fluctuations indicate that the rankings of these countries are highly sensitive to changes in the weighting of population and area criteria when using the WP method. The ranking using the WASPAS method can be seen in Figure 6 below.

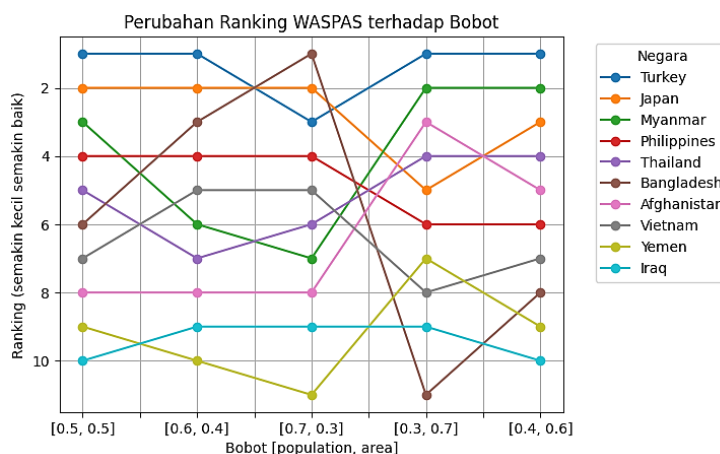


Figure 6. The Ranking Using The WASPAS Method

Figure 6, titled ‘Changes in WASPAS Rankings Based on Weighting,’ shows the dynamics of country rankings based on the WASPAS (Weighted Aggregated Sum Product Assessment) method with variations in population and area weighting. The horizontal axis (X) shows different weight combinations, ranging from [0.5, 0.5] to [0.4, 0.6], while the vertical axis (Y) represents the ranking, where lower numbers indicate better rankings. From the graph, it is evident that Turkey (dark blue) consistently ranks at the top (1 or 2) in most weighting scenarios, indicating stability and superior performance. Japan (orange) also maintains a high position, though with some fluctuations. The Philippines (red) exhibits an interesting movement pattern, briefly reaching the 4th rank before dropping to the 6th rank. Bangladesh (brown) experienced the most drastic ranking changes, rising significantly at the beginning, then plummeting sharply as the area weight increased at [0.3, 0.7], and then rising again. Other countries such as Myanmar (green), Thailand (purple), Afghanistan (pink), and Vietnam (grey) show movement within the mid-range rankings. Meanwhile, Yemen (yellow) and Iraq (light blue) tend to remain at lower rankings, although Yemen shows a drastic decline at the point [0.7, 0.3]. These patterns indicate how each country's ranking is sensitive to relative changes in the weighting between population and area criteria when using the WASPAS method.

After performing the ranking of the three MCDM methods above based on the specified weighting criteria, the next step is to assess the Spearman correlation between the multi-criteria decision-making methods (SAW, WP, and WASPAS) for each weight combination between population and area. The Spearman correlation measures the strength and direction of the monotonic relationship between two variables, where values close to 1 indicate a very strong positive correlation (very similar rankings), and values close to 0 indicate no correlation. Figure 7 shows the resulting Spearman correlation values.

Weight	SAW vs WP	SAW vs WASPAS	WP vs WASPAS
0 [0.5, 0.5]	0.983104	0.996597	0.991613
1 [0.6, 0.4]	0.981160	0.996111	0.991937
2 [0.7, 0.3]	0.983266	0.996921	0.992261
3 [0.3, 0.7]	0.992504	0.998379	0.995584
4 [0.4, 0.6]	0.987561	0.995300	0.995503

Figure 7. The Spearman Correlation Between The Multi-Criteria Decision-Making Methods

Based on Figure 7, it can be observed that all Spearman's correlation values are very high, above 0.98 for all comparisons and weight combinations. This indicates a very strong agreement in rankings among the three methods (SAW, WP, and WASPAS) in this case. The correlation between WP and WASPAS is very high, ranging from 0.991613 to 0.995584, confirming the strong similarity in rankings between the two. It should be noted that for the weight combination [0.3, 0.7] (where the area weight is more dominant), the correlation values tend to be slightly higher for all method pairs compared to other weight combinations. This indicates that when the area criterion is emphasised, the three methods produce even more consistent rankings with each other. For clarity, the following bar chart visualises the Spearman rank correlation between MCDM methods.

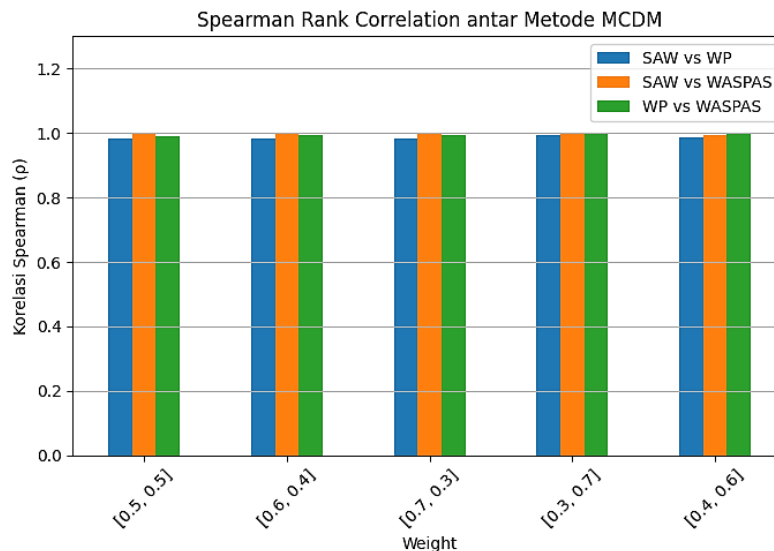


Figure 8. The Spearman rank correlation between MCDM methods

Figure 8 shows the results of Spearman's correlation analysis between pairs of multi-criteria decision-making (MCDM) methods used, namely Simple Additive Weighting (SAW), Weighted Product (WP), and Weighted Aggregated Sum Product Assessment (WASPAS). This analysis was conducted for various combinations of weights between population and area criteria, represented on the horizontal axis (Weight). The vertical axis shows the Spearman correlation coefficient values. From Figure 8, it can be observed that the Spearman correlation coefficient values for all method pairs (SAW vs WP, SAW vs WASPAS, and WP vs WASPAS), especially at weights [0.3:0.7] and for all weight combinations, are close to 1.0.

Therefore, in ranking using the MCDM method, the SAW vs WASPAS method is better used in this study with a spearman correlation value of 0.998379. Thus, the ranking of 10 countries in Figures 4 and 6 is the final result of this study, where Turkey ranks first among the 50 countries in the ASIA region.

4. CONCLUSION

Market potential analysis using K-Means Clustering and Multicriteria Decision Making (MCDM) shows that dividing the data into three clusters is optimal based on the elbow method and high silhouette score (0.8862). The first cluster includes areas with low population and small area, the second cluster is larger with low to moderate population, and the third cluster contains extreme points (very high population/small area or vice versa) identified as outliers. For further analysis, this study focused on the first cluster using the SAW, WP, and WASPAS methods with five weighting scenarios. The ranking results show that Turkey consistently ranks at the top in all three methods, while other countries like Bangladesh show high sensitivity to changes in weighting. The consistency of rankings across methods is very high, as indicated by Spearman's correlation values approaching 1.0 (the highest between SAW and WASPAS at 0.998379 for weights [0.3, 0.7]), indicating that the three methods produce very similar preference orders. Therefore, SAW and WASPAS are recommended as the best methods for this study, with the final ranking placing Turkey as the top country among 50 countries in the Asian region.

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