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Decision-Making Framework for Improving Bank Performance in Emerging Markets: The Analysis of AHP-TOPSIS and AHP-GRA Models

Abstract: This study utilizes the Analytic Hierarchy Process (AHP) in combination with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Grey Relational Analysis (GRA) models to thoroughly assess the performance of banks in China, India, Pakistan, and Thailand. The integrated results offer significant insights into the relative rankings of various banks in each country. In China, Bank of China Ltd (BOC) emerges as the top performer, setting a benchmark for others. Similarly, in India, the State Bank of India is consistently identified as the leading bank. The National Bank of Pakistan stands out as the top performer in Pakistan. In Thailand, despite minor deviations in results, Kasikornbank PCL (KBANK) consistently shows strong performance. The alignment of results between AHP-TOPSIS and AHP-GRA underscores the reliability of both models, providing stakeholders and decision-makers with a comprehensive understanding of bank performance. This enables them to identify benchmarks, leverage strengths, and address areas for improvement within each country's banking sector.

Keywords: MCDM, AHP, TOPSIS, GRA, Emerging Market, Bank Performance.

JEL Classification: E50, F16, F18.

1. Introduction

Bank performance measurement is a crucial task for researchers and practitioners to better understand the banking sector's overall health and stability. Traditional financial ratios, such as Return on Assets (ROA) and Return on Equity (ROE), have been widely used to assess banks' returns. However, these ratios are limited when providing a comprehensive assessment of banks' performance, as they capture only a limited range of aspects of their performance. In recent years, Multi-Criteria Decision Making (MCDM) approaches have been increasingly used to evaluate the performance of banks. The MCDM approaches provide a more comprehensive assessment of bank performance, considering multiple criteria and aspects of performance, such as financial performance, risk management, and social responsibility. A study by Guru and Mahalik (2019) applied different MCDM techniques to evaluate the performance of commercial banks in India and found that it provided a more comprehensive assessment of bank performance than traditional financial ratios. One popular MCDM approach used in performance evaluation is the Analytic Hierarchy Process (AHP) (Hussain, Ali, Hussain & Lu (2019. It is a structured decision-making method that uses pairs of criteria comparisons to assess the relative importance of different criteria Kaličanin, Grubišić & Kamenković(2023).

Another MCDM approach widely used in evaluating banks' performance is TOPSIS. It uses a weighted linear combination of criteria to classify alternatives according to their proximity to the ideal solution. Grey Relational Analysis (GRA) is another method to analyze complex systems with multiple variables. It is used to determine the relative importance of different variables and to identify the most significant factors that affect the bank's performance. However, traditional bank performance measurement methods, such as financial ratios, have limitations because they need to account for the complexity and versatility of bank performance. As a result, assessing their performance is essential for ensuring the financial system's stability and making informed decisions about investing in the banking sector (Ozili and Alonso, 2024).

This study concentrates on the area of multi-criteria decision-making in the assessment of banks' performance. The study aims to evaluate the performance of emerging markets banks including China, India, Thailand and Pakistan. It also examines past research in MCDM to identify research gaps. The findings suggest various researchers have used different MCDM techniques to assess banks' performance against different criteria. In the present study, we assess the performance of banks in emerging economies by analyzing their annual reports spanning from 2019 to 2022, which are publicly available. To conduct this evaluation, we employ three multi-criteria decision-making tools: (AHP) (Hussain, Xuetong, Hussain, Khoja, & Zia, 2021), (TOPSIS), and (GRA). AHP aids in determining the relative weights of various criteria, while TOPSIS and GRA are utilized to measure and rank the performance of commercial banks in emerging markets. Additionally, we conduct a comparative analysis between TOPSIS and GRA methodologies (Hussain and Hussain, 2024).

The main objective of this study is to propose a new method for assessing bank performance that considers multiple dimensions of performance and allows for the integration of qualitative and quantitative information about the emerging market banking sector. Specifically, the study aims to apply MCDM approaches, such as AHP, TOPSIS, and GRA, to handle the uncertainty and vagueness in the evaluation of bank performance and rank them accordingly and then compare the performance of banks using the proposed AHP-GRA and AHP-TOPSIS with financial variables to evaluate the effectiveness of the proposed method. This study will provide recommendations to bank clients, regulators, and investors on how to use the proposed methodology to evaluate banks' performance and investment strategies (Omankhanlen, Ilori, Isibor & Okoye, 2021).

By using AHP-TOPSIS and AHP-GRA, the study focused on evaluating the performance of ten commercial banks in each country and eight banks from Thailand under scrutiny. The findings revealed that specific banks stood out as top performers in their respective countries. In China, the Bank of China Ltd (IBC) emerged as the best-performing bank. In Pakistan, the National Bank of Pakistan (NBP) secured the top spot and was ranked first. Meanwhile, the State Bank of India (SBI) was positioned as the leading bank in India, and Kasikornbank (Kbank) claimed the top spot in Thailand.

However, the rankings of other banks exhibited slight variations due to methodological disparities in the assessment process. Nevertheless, the overall outcomes of the study pointed towards specific banks that were considered the most successful within their respective countries. Bank of China Ltd (BOC) in China, State Bank of India (SBI) in India, National Bank of Pakistan in Pakistan, and Kasikornbank (Kbank) in Thailand were identified as the most successful and top-ranking banks in their nations.

Conversely, the study also identified banks that were perceived as the worst-performing within this evaluation framework. Ping An Bank Co Ltd (PAB) in China, IDBI Bank Ltd in India, Faysal and Meezan Bank in Pakistan, and Kiatnakin Bank in Thailand were designated as the least successful banks based on the AHP-TOPSIS and AHP-GRA analysis.

The rest of the study comprises five sections: section two gives a literature review. Section three sets out data and methodologies such as AHP, TOPSIS, and GRA. The results and discussion are displayed in section four. Finally, conclusions are drawn in section five.

2. Literature Review

The Multi-Criteria Decision-Making technique is a systematic approach for evaluating and ranking alternative solutions based on multiple criteria. MCDM techniques are widely used in various fields, including engineering, economics, management, environmental sciences, and finance. Ture, Dogan & Kocak (2020) present an evaluation of the performance of 27 EU Member States in achieving the objectives of the EU 2020 strategy for smart, sustainable, and inclusive growth. The evaluation is based on a multi-criteria decision-making method considering 22 indicators in various economic, financial, demographic, educational, and innovative fields. The findings show that new EU member countries such as Slovenia and Romania perform better than some of the 15 EU countries. Basset, Ding, Mohamed & Metawa (2020) introduce a financial performance assessment model for manufacturing industries that uses MCDM tools and financial ratios to rank Egypt's top 10 steel firms. The results are presented as VIse Kriterijumska Optimizacija I KOmpromisno Resenje (VIKOR)) and TOPSIS with similar results.

Marques, García & Sánchez (2000) focus on using multi-criteria decision-making methods in financial decision-making, focusing on value-based and outranking relations approaches. It presents an overview of the contributions of these methods in financial applications from 2000 to 2018, highlighting current developments and open research issues. Celik, Erdogan and Gumus (2016) presents an evaluation method for determining "green" logistics service providers. The method combines fuzzy TOPSIS and GRA, using expert opinions to determine criteria weights. The method was applied to a case study of five Turkish providers in Istanbul and found similar results after comparing fuzzy TOPSIS and fuzzy VIKOR. Nguyen, Tsai, Kumar & Hu (2020) focused on ranking the agriculture sector stock on the Vietnam Stock Exchange Market using a combination of methods, AHP, GRA, and TOPSIS. The results showed that the Hong Ha Food Investment Development (HSL) stock was ranked the highest, and the rankings produced by all methods had strong correlation values.

Naseem, Yang & Xiang (2021) used a combination of GRA and TOPSIS methods in choosing the best logistics service provider for an e-commerce company in Pakistan, which considered seven criteria of logistics suppliers and selected the best alternatives among four logistics providers. Tekin and Keskin (2021) attempted to build a business portfolio throughout the pandemic using TOPSIS and GRA. Portfolio performance was compared and found that the lowest-performing portfolio had the largest average positive change. The study found that the performance of portfolios created through TOPSIS and GRA is higher than other alternatives. Sama, Kosuri & Kalvakolanu (2020) analyzed the performance of the Indian private bank sector using multiple criteria decision-making techniques, including Criteria Importance Through Inter Criteria Correlation (CRITIC), TOPSIS, and GRA. The results revealed that HDFC was the best-performing bank among other alternatives, followed by Bandhan Bank as the second-best-performing bank. The study suggests that private sector banks should improve their performance to compete with the best public and foreign banks and attract investment (Rakshit and Bardhan, 2020).

Ho (2006) applied GRA to measure the performance of three Taiwanese investment trust banks. The results were compared against the Financial Statement Analysis (FSA), and the same results were achieved. Mayakkannan and Jayasankar (2020), Pekkaya and Demir (2018), Wanke, Azad & Barros (2016), and Chen and Hsu (2016) used the CAMELS rating system and bank ratios to assess banks' returns about six dimensions: capital adequacy, asset quality, management, profits, liquidity, and market risk sensitivity. According to the study, asset quality is considered the most important aspect, followed by earnings, liquidity, and management. All dimensions are interdependent and must be considered together in assessing a bank's performance. Gavurova, Belas, Kocisova & Kliestik (2017) used various MCDA techniques to evaluate the performance of Czech and Slovakian banks. They found a perfect correlation between all the techniques and similar findings in past research.

By using ANP and GRA, Liu et al. (2012) rank the overall performance based on competing suppliers. Ecer and Boyukaslan (2014) used GRA to assess the financial performance of football clubs, and Mandic, Delibasic, Knezevic & Benkovic (2014) used FAHP (Fuzzy Analytical Hierarchy Process) and TOPSIS methods to assess Serbian banks' financial parameters. The results showed that equity and profit before tax were the most critical parameters of this assessment. The results suggest that it may be helpful for bank executives, investors, and stakeholders better to understand the financial health and performance of Serbian banks. The previous studies show that the TOPSIS and GRA are widely used MCDM techniques to assess the performance of various investments, including mutual funds in Taiwan and technology companies traded in the Istanbul Stock Market (Chang, Lin, Lin & Chiang, 2010; and Bulgurcu 2012). The authors of these studies attempted to improve the accuracy of the assessment results by incorporating other methods, such as the Fuzzy Analytical Hierarchy Process (FAHP), and by comparing the results obtained from different MCDM techniques, such as the VIKOR method.

3. Data and Methodology

This paper assessed and categorized bank performance using several factors. The paper analysed data collected from secondary sources, primarily annual bank reports issued for 2019-2022. The data included financial information on banks such as Net Assets, Total Liabilities, Total Equity, Cash from Operating Activities, Cash from investing Activities, and Gross profit. These data were used to evaluate the weight of the variables examined in the study.

The use of MCDM, AHP, TOPSIS, and GRA methodologies allows us to deal with multiple factors and fulfill the purpose of the study. The study was reviewed with MCDM tools such as AHP-TOPSIS and AHP-GRA. AHP was used to calculate the weight of the variables, while TOPSIS and GRA were used to measure and rank the performance of the banks.

Two factors were considered in selecting Decision-Making Units (DMUs), Homogeneity and number of DMUs. Homogeneity refers to the similarity of the objectives of the DMUs. The 38 emerging countries banks share the same objectives, so they were selected as DMUs. It was decided to consider three input variables and three outputs. Input variables are factors that result in output variables. In such cases, the input variables are Total Assets (X1), Total Liabilities (X2), and Total Equities (X3). Production variables are cash from operating activities (Y1), Cash from investing activities (Y2), and Gross profit (Y3). These variables were selected based on literature analysis of past bank performance studies. The researchers selected these variables because they are seen as essential indicators of bank performance. Input variables should explain the bank's ability to generate resources, while output variables should explain the bank's ability to use resources effectively. These variables are considered when assessing and comparing bank performance (Hussain etl. 2018).

3.1. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) was developed by Saaty (Saaty,1980). The Analytic Hierarchy Process quantifies subjective judgments of decision-makers by assigning numerical values that depict the relative importance of the elements being compared. The magnitude of preference in pairwise comparisons as shown in Table 1 indicates the strength of preference.

Once these pairwise comparisons are completed, they form a matrix known as the pairwise comparison matrix. The eigenvector of this matrix provides the weights of the components under comparison. In this process, each element of the pairwise comparison matrix is initially divided by the sum of its respective column. Subsequently, the sums of the rows are calculated and normalized by dividing each sum by the total sum of all rows to ensure their collective sum equals 1. These normalized row sums yield the weights of the components under consideration.

The AHP efficiently extracts information on the judgement of preferences in a clear and understandable way. AHP uses a 1-9 preference scale to compare information. The pairwise comparison matrix is developed using bank management information, as shown in Tables 2 and 3. AHP also helps to determine the consistency of the evaluated result by calculating the weight factor for each set of criteria. The heavier it gets, the more important it becomes. In this study, AHP calculates the weight from input and output variables.

Table 1: Comparison of scale source

Weights	Definition	Explanation
1	Important Equally	Two criteria are equally important to the goals.
3	Weakly Important	The decision favours slightly one over the other.
5	Strongly Important	The judgment strongly favours one over the other.
7	Vary strongly important	The judgment very strongly favoures one over the other.
9	Extremely Important	The judgment is of absolute importance over the other.
2,4,6,8	Intermediate	The judgment is neutral for both criteria.

Table 2: Pair comparisons for input variables

	Total Assets (X1)	Total Liabilities (X2)	Total Equities (X3)
Total Assets (X1)	1	5	4
Total Liabilities (X2)	2	1	5
Total Equities (X3)	1/4 = 0.250	0.5	1

Table 3: Pair comparisons for output variables

	Cash from operating activities (Y1)	Cash from investing activities (Y2)	Gross Profit (Y3)
Cash from operating activities (Y1)	1	4	5
Cash from investing activities (Y2)	0.25	1	4
Gross Profit (Y3)	0.20	4	1

The normalization of a decision matrix is a technique used to ensure that all of the criteria in the matrix are on a comparable scale.

$$A_{nxn} = \begin{bmatrix} a_{11} & a_{12....} & a_{1n} \\ a_{21} & a_{22....} & a_{2n} \\ a_{n1} & a_{n2....} & a_{nn} \end{bmatrix} \quad (1)$$

This is often done using a linear normalization technique, which may be expressed in the following equation:

$$x_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (2)$$

where i = 1,2,3…...n

And j=1,2, 3....…..n

And x is the normalized value of $_{(i,j)}{}^{th}$ term choice matrix component.

For non-beneficial normalization, expressed by the following equation:

$$x_{ij} = 1 - \frac{x_{ij}}{x_j^{max}} \quad (3)$$

where i = 1,2,3…...n

And j=1,2, 3……n

And x is the normalized value of $_{(i,j)}{}^{th}$ term decision matrix component.

To construct a weighted normalized decision matrix, a common method is to use the average elements in each row of the normalized pairwise comparison matrix. This may be done with the following equation:

$$W_i = \frac{\sum_{j=1}^{n} C_{ij}}{n} \quad (4)$$

i= 1,2, 3……...n and C_{ij} is the normalized value.

$$W = \begin{bmatrix} W1 \\ W2 \\ . \\ . \\ Wn \end{bmatrix} \quad (5)$$

Calculation of the Eigenvector and Row matrix by the formula below.

$$E = \frac{N_{th} \text{ root value}}{\sum N_{th} \text{ root value}} \quad (6)$$

Row matrix = $\sum_{j=1}^{n} a_{ij} * e_{ij}$ (7)

The maximum Eigenvalue is indicated by (λmax) that can be calculated by the following formula

$$\lambda_{max} = \frac{Row\ matrix}{E} \quad (8)$$

The Coherence Index (CI) and the Coherence Ratio (CR) can be calculated as follows.

CI = $\frac{\lambda_{max}-n}{n}$, where (n) represents the number of items compared. (9)

And CR = $\frac{\text{CI}}{\text{RI}}$ (10)

The random index (RI) is a value used to assess the consistency of pairwise comparison matrices. The RI is generated randomly, and its value is determined by the number of elements being compared. Table 4 shows the RI values for different "n" values representing the number of components compared. This study used six criteria in the analysis and derived individual weights of the input and output variables. This study selected an RI value of 0.58 for the input and output criteria and determined the value from "n" to 3 in both cases. It suggests the study used a 3x3 pair comparison matrix to evaluate the consistency criteria. The value of 0.58 is within the range of acceptable values with the random index values.

Table 4: Criteria weights for random index

N	1	2	3	4	5	6
RI	0	0	0.58	0.90	1.12	1.24

3.2. TOPSIS

TOPSIS is a multi-criteria decision-making method introduced by Hwang and Yoon (1981). It ranks alternatives based on their similarity to an ideal solution, defined as a solution that maximizes the benefit criteria and minimizes the cost criteria. The algorithm is applied by defining a set of decision criteria, then normalizing the data for each criterion, and finally calculating the relative closeness of each alternative to the ideal solution. The alternative closest to the ideal solution is considered the best solution. This method is often used when selecting the best option from a set of alternatives, such as the best bank for performance.

Below are the TOPSIS steps for the calculation of the decision matrix criteria for a positive ideal solution:

$(D^+) = \{D_1^+, D_2^+, \dots \dots . . D_n^+\}$, where, D_j^+=$\{(\max(D_{ij})\ if\ j\ \in J; (\min(D_{ij})\ if\ j\ \in J^{'})\}$ (11)

To the negative ideal solution is the following:

$(D^-) = \{D_1^-, D_2^-, \dots \dots . . D_n^-\}$, where, D_j^-=$\{(\min(D_{ij})\ if\ j\ \in J; (\max(D_{ij})\ if\ j\ \in J^{'})\}$ (12)

where J stands for the favourable positive solution, while J is related to the unfavourable solution.

Calculating positive and negative ideal solutions is described in the following equations.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(D_{ij} - D_j^+)^2}, \text{ i=1,2, 3.........m,} \quad (13)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(D_{ij} - D_j^-)^2}, \text{ i=1,2, 3.........m,} \quad (14)$$

where S_i^+ is the separation from positive ideal alternative solutions. Similarly, S_i^- means the separation of ideal negative alternatives.

$$R_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} \quad (15)$$

where I =1,2, 3….m and j = 1,2, 3……n and R_{ij} are original and normalization matrix.

For normalization following linear equation has been utilized.

$$x_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (16)$$

where i = 1,2,3…...n and j=1,2, 3....……n and x is the normalized value of $_{(i,j)}{}^{th}$ term choice matrix component. For non-beneficial normalization is as below.

$$x_{ij} = 1 - \frac{x_{ij}}{X_j^{max}} \quad (17)$$

where i = 1,2,3…...n and j=1,2, 3……n and x is the normalized value of (i,j)th term decision matrix component.

The calculation weight normalization matrix is multiplied by the weight with the normalized matrix. This study uses the AHP technique to calculate weights.

$$D_{ij} = W_i * R_{ij} \tag{18}$$

where D_{ij} represent the weighted normalization matrix and W_i represent the weight of criteria.

For determining the positive and negative ideal solutions, the maximum value in the weighted normalized decision matrix is regarded as the positive ideal solution. In contrast, the minimum value represents the negative ideal solution.

The relative proximity of ideal solutions (CCi) can be computed using the following equation.

$$CC_i = \frac{S_i^-}{S_i^- + S_i^+}, 0 \leq \text{Ci} \leq 1 \tag{19}$$

After calculating (CCi), the rank will be calculated between the different alternatives. The highest value is equal to one.

3.3. Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) is a statistical method used to analyze and compare datasets of both quantitative and qualitative information. It was initially proposed by Deng (1989) and is widely used in various fields such as engineering, management, economy, and finance. The main idea behind GRA is to establish a grey relational grade (GRG) between two variables, which can be used to measure their degree of correlation. The results of GRA can be used to make decisions, identify the problem, and solve them. The major benefits of this methodology are non-parametric and relatively compared to other measurement approaches to modeling and ranking alternative options.

Huang and Liao (2003) proposed three methods for normalizing data to examine whether a criteria set is better when higher, smaller, or falls within a range between higher and smaller. If a higher value is considered to be better, normalization is carried out by dividing each value in the dataset by the maximum value in the dataset. This results in a new data set with values ranging from 0 to 1, with one as the highest value in the original data set. This method is known as "scaling to unity" or "unit scaling."

Normalization is performed by following the equation when a higher value is considered better.

3.3.1. Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) is a method used to assess the connection between two discrete series within a grey system, with the capacity to recognize changes in this relationship over time. GRA can pinpoint weak signals within various pertinent variables by analysing random factor series. The first step in GRA is feature extraction, which involves three equations.

a) The Greater-the-Better (GTB) Expectation Equation:

The greater-the-better equation is used when higher values indicate better performance or desirability. It measures the degree of similarity between two sequences of data. The equation is as follows:

$$x_g^*(k) = \frac{x_g^0(k) - \min x_g^0(k)}{\max\ x_g^0(k) - \min x_g^0(k)} \tag{20}$$

Where, $x_g^*(k)$ is the GRA coefficient sequence after data preprocessing, $\max x_g^0(k)$ indicate the highest value of $x_g^0(k)$, and $\min x_g^0(k)$ represent the smallest value of $x_g^0(k)$.

b) The smaller-is-better (STB) Expectation Equation:

When lower values indicate higher performance or desire, the STB equation will be utilized. With the aim of minimizing values, it measures how similar two data sequences are to one another. The equation looks like this:

$$x_m^*(k) = \frac{\max\ x_m^0(k) - x_m^0(k)}{\max\ x_m^0(k) - \min x_m^0(k)} \tag{21}$$

Where, $x_m^*(k)$ is the GRA coefficient sequence after data preprocessing, $\max x_m^0(k)$ indicate the highest value of $x_m^0(k)$, and $\min x_m^0(k)$ represent the smallest value of $x_m^0(k)$. The best value better if it is nearer to desirable value $x_i^*(k)$.

c) The nominal the best Expectation Equation:

where a particular value is likely to fall somewhere between higher and smaller. The normalization of data is as follows:

$$X_i^*(k) = \frac{|x_i^0(k) - x_i^0|}{\max\ x_i^0(k) - x_i^0} \tag{22}$$

3.3.2. Deviation Sequence

The deviation sequence of the references sequence is as follows:

$$\Delta_{0i}(K)=\|X_0^*(K) - X_i^*(K)||\tag{23}$$

$$\Delta_{max} = max_{\forall j\varepsilon i}\ max_{\forall K}||X_0^*(K) - X_j^*(K)||\tag{24}$$

$$\Delta_{min} = min_{\forall j\varepsilon i}\ min_{\forall K}||X_0^*(K) - X_j^*(K)||\tag{25}$$

3.3.3. Grey Relational Coefficient

The Grey Relational Coefficient (GRC) is used to calculate the degree of similarity between the ideal sequences. It quantifies how closely one sequence looks like another, with a higher GRC indicating a stronger relationship. GRC can be calculated using following equation.

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta.\Delta_{max}}{\Delta_{0i}(k) + \zeta.\Delta_{max}}\tag{26}$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence. ζ is the identification coefficient it value must be $\zeta\ \varepsilon$ {0,1} usually 0.5 is considered. After getting the GRC values, the grey relational grade is calculated by following.

3.3.4. Grey Relational Grade (GRG)

It is used to rank and compare multiple sequences and using their Grey Relational Coefficients. The GRG will be calculated by following equations.

$$\gamma_i = \frac{1}{n}\sum_{k=0}^{n} i\ \zeta_i(k)\tag{27}$$

Figure 1 shows a continuous workflow for assessing bank performance through a combination of AHP-TOPSIS methods. The workflow is divided into 1 to 10 steps, each providing more details on the various components involved in the process. These steps include the establishment of a hierarchy of criteria, the determination of the relative importance of criteria, and the assessment of alternatives. Overall, this framework aims to provide a systematic and comprehensive approach to evaluating the performance of different options.

This framework offers a systematic and comprehensive approach to assessing the performance of different banks and identifying areas for improvement. Figure 2 depicts a workflow for assessing bank performance using AHP and GRA methods. The workflow consists of 10 steps which include: defining the problem and decision criteria, collecting data, determining the weights of the criteria, generating the grey relational grade, ranking the alternatives, selecting the best alternative, assessing the robustness of the results, identifying the key factors that influence the performance of the bank, and implementing the improvement plan.

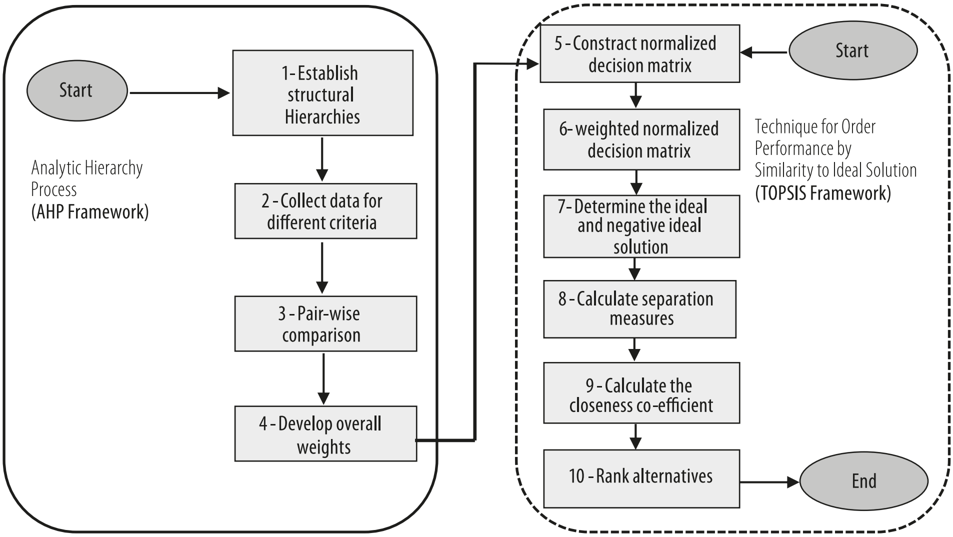
4. Empirical Results

4.1. AHP Results

The study uses AHP to evaluate the performance of banks. It demonstrates that the method effectively determines the relative importance of various criteria using the Likert scale. It is a journal opinions and judgement on the level of importance of each factor, and this information was used to create a Pairwise Comparison Matrix for both input and output variables. This matrix was then used to calculate input and output variable weights. The results indicated that AHP is a helpful tool for evaluating bank performance, as it allows for considering multiple criteria and helps check the consistency ratio (CR).

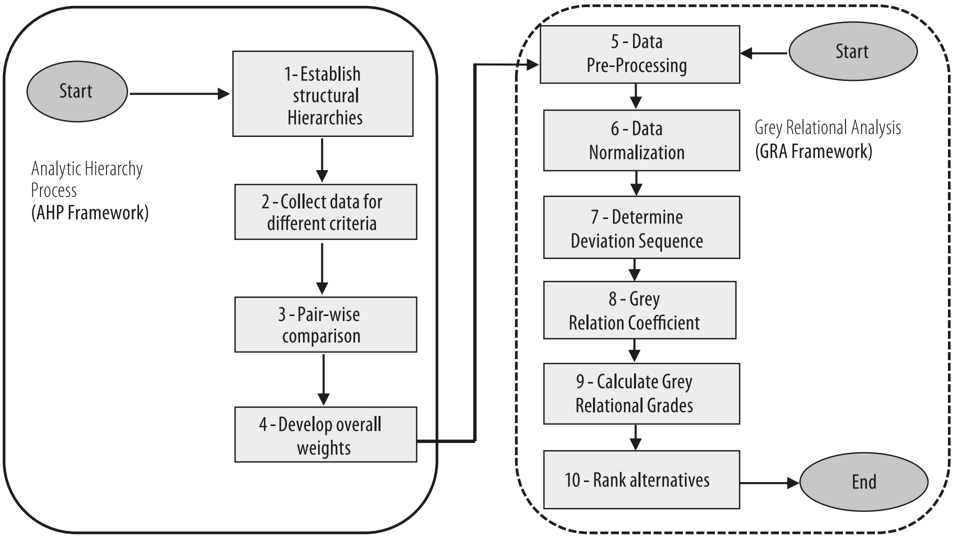
The Analytic Hierarchy Process was used to evaluate the performance of banks in emerging markets. The method effectively measured the relative significance of various criteria and ranked the banks based on their performance. Importantly, the analysis did not identify any inconsistency or calculated coherence ratio (CR) issues for both input and output variables. The CR values obtained were -2.519 for the input and -2.568 for the output variables. Typically, in AHP, consistency ratios help assess the reliability of the judgments and computations. A consistency ratio below 0.10 is generally deemed acceptable for the analysis to proceed, as it suggests a satisfactory level of consistency in the pairwise comparisons made during the evaluation process. The negative values of the CR are usual in traditional AHP interpretation, as CR values are typically non-negative and indicate the level of consistency in the judgements made during the AHP process.

Figure 1: An integrated AHP-TOPSIS Framework



Source: Agyemang, Kwofie & Baum (2022)

Figure 2: An integrated AHP-GRA Framework



Source: Agyemang, Kwofie & Baum (2022)

The AHP weighted scores (WAHP) and consistency ratio are present in Table 5. These weighted values are utilized by the TOPSIS and GRA methods. All four emerging markets banks, were considered in the study. The findings of these methods make it possible to compare the performance of emerging market banks.

Table 5: Weights criteria alternatives and consistency ratio for input and out variables

Input	Weight	λmax	CR
X1	0.729	0.539	
X2	1.100	CI= -1.461	CR=-2.519
X3	0.144	RI=0.58	
Output	Weight	λmax	CR
Y1	0.544	0.510	
Y2	1.833	CI= -1.489	CR= -2.568
Y3	0.227	RI=0.58	

4.2. TOPSIS Results

This study uses TOPSIS to determine the best input and output variables decision. The preferred decision should be the one that is the shortest distance from the positive ideal solution (PIS) and the furthest from the negative ideal solution (NIS). Input variables include total assets, total deposits, and liabilities, while output variables include investments, advances/loans, and total income with tax deductions. The method uses these variables to determine the best decision by comparing the distance of each alternative decision from the PIS and NIS. In this study, a decision matrix was created using bank data. The data were subsequently normalized by using linear normalization technique. Next, weights were multiplied with the normalized data to create a weighted normalized matrix. The positive ideal solution (PIS) and negative ideal solution (NIS) were then determined, and the relative closeness of each bank to the ideal solution was calculated. The results of this calculation and the banks were ranked depending on their proximity to the ideal solution. For Chinese banks, the Positive Ideal Solution for the criteria X1, X2, X3, and Y1, Y2, and Y3 are 0.001, 0.144, 0.545, 1.833, 0.277, respectively. Similarly, the Negative Ideal Solutions for the same criteria are 0.098, 0.950, 0.018, -0.809, -6.786, and 0.035, respectively. Similarly, for Indian banks, the Positive Ideal Solution for the criteria X1, X2, and X3 are 0.729, 0.000, 0.144, whereas for Y1, Y2, and Y3 they are -18.184, -1.462.000, and 0.009, respectively. For Pakistani banks, the Positive Ideal Solution for the criteria X1, X2, and X3 are 0.729,0.000,0.144, whereas for Y1, Y2, and Y3 they are 0.545,13.92,and 0.227, respectively. And the same results for Thailand we can see in table 6.

Table 6: The ideal (best) and ideal (worst) solution for banks

			China			
D^+	0.729	0.000	0.144	0.545	1.833	0.227
D^-	0.098	0.950	0.018	-0.809	-6.786	0.035
			India			
D^+	0.729	0.000	0.144	0.545	1.833	0.227
D^-	0.044	1.038	0.012	-18.184	-462.000	0.009
			Pakistan			
D^+	0.729	0.000	0.144	0.545	13.922	0.227
D^-	0.149	0.877	0.029	-0.003	1.833	0.054
			Thailand			
D^+	0.729	0.000	0.144	0.545	1496.121	0.227
D^-	0.068	0988	0.013	-2.048	1.833	0.021

The study then calculates a separation measurement for each alternative from the Positive and Negative Ideal Solutions. It computes the relative closeness to the ideal solution of each alternative.

Table 7 indicates the combined results of AHP-TOPSIS. These results showed the assessments of the performance of banks in China, India, Pakistan and Thailand. The AHP method is used to determine the relative weighing criteria, while the TOPSIS method is used to compare the performance of each bank to an ideal solution. After combining the results of these two methods, the study found that Bank of China Ltd (BOC) had the highest value of the closeness coefficient (CCi). The study observed that Bank of China Ltd (BOC) had the highest CCi of 4.9452, which indicates that it is the best-performing bank among the other alternatives in China. Bank of China Ltd,is taken as a benchmark for other banks. Table 8 shows the rankings and other banks results based on their CCi. On the other hand, Ping An Bank Co Ltd (PAB) had the lowest value of CCi, which is 0.001, indicating that it is the worst-performing bank among the alternatives. So this DMU (Decision Making Unit) is ranked last.

Moreover, the study examined the performance of various banks in India using a measures of AHP-TOPSIS, higher values of CCi indicating better performance. Based on the results, the State Bank of India (SBI) had the highest CCi value, which was 458.218. This high CCi value suggests that State Bank of India is the best-performing bank among the alternatives considered in the study. In essence, SBI can be considered as the benchmark or the top performer against which other banks can be compared. This means that, in terms of the criteria used to assess their performance, SBI outperformed all the other banks in the study and can serve as a reference for excellence in the Indian banking sector. Conversely, IDBI Bank Ltd had the lowest CCi value. This extremely low CCi value indicates that IDBI Bank is the worst-performing bank among the alternatives considered in the study. In other words, it ranked at the bottom in terms of performance based on the chosen criteria. This suggests that IDBI Bank faces significant challenges and shortcomings in comparison to its peers. These results are consistent with Guru and Mahalik (2019) who applied different MCDM techniques to evaluate the performance of commercial banks in India and found that State Bank of India outperformed the other alternative banks in India.

Similarly, the study found that the National Bank of Pakistan performed the best among the other banks, establishing itself as the top performer and a benchmark for others. On the other hand, Faysal Bank Ltd showed the lowest performance with a CCi value of 0.001, indicating it as the worst-performing bank among the other alternatives study in thid paper. and hence, it was ranked last. The study revealed that Kasikornbank PCL (KBANK) of Thailand performed better than other banks in the country and that it was the ideal bank for customer. The study estimated the probability of strong economic conditions of a bank such as total assets, total investments, and fewer liabilities, which lead to an increase in the performance of banks. It helps banks earn more from investment activities and other investments. The study also examined? strong regulation and oversight, which help to ensure the stability and safety of the banking system, as well as diversified sources of income, such as income from different investment activities, advances, and investment products. The results suggest that after comparing the separation measurements of each option from the positive and negative ideal solutions and computing the relative closeness to the ideal solution of each alternative, the researchers can determine which alternative (i.e. bank) is the best performer. This study helps them determine which banks perform well based on multiple metrics and which banks may have challenges in certain areas.

Table 7: Closeness Coefficient Index and rank of the banks

DMU#	DMU Name	S_i^+	S_i^-	$CC_i = \frac{S_i^-}{S_i^- + S_i^+}$	Rank
		China			
1	Industrial and Commercial Bank of China Ltd	8.6743	0.7431	0.8288	8
2	China Construction Bank (CCB)	6.0587	2.3760	2.7682	3
3	Agriculture Bank of China (ABC)	4.7919	3.1661	3.8268	2
4	Bank Of China Ltd (BOC)	3.2634	3.7853	4.9452	1
5	China Merchants Bank Co Ltd (CMB)	3.6787	0.6813	0.8665	7
6	Ping An Bank Co Ltd (PAB)	2.4259	0.0000	0.0001	10
7	Bank of Communications Co Ltd (BOcom)	3.1064	1.2375	1.6359	5
8	Industrial Bank Co Ltd (IBC)	1.3183	0.9965	1.7524	4
9	China Everbright Bank Co Ltd (CEB)	2.9988	0.1742	0.2323	9
10	Postal Savings Bank of China Co Ltd	4.0132	1.2008	1.5000	6
		India			
1	State Bank Of India (SBI)	38.2338	446.5396	458.2188	1
2	HDFC Bank Ltd	28.3409	153.5263	158.9434	2
3	ICICI Bank Ltd (ICBK)	463.8340	5.2779	5.2892	9
4	Bank of Baroda Ltd (BOB)	15.0539	99.4063	106.0097	3
5	Axis Bank Ltd (AXBK)	270.8653	32.8872	33.0086	7
6	Central Bank of India Ltd (CBI)	4.0776	9.1262	11.3644	8
7	IDBI Bank Ltd (IDBI)	1.6588	0.0000	0.0000	10
8	Bank of India Ltd (BOI)	6.5735	44.3147	51.0561	6
9	Union Bank of India	11.5624	72.9367	79.2448	5
10	Punjab National Bank (PNBK	10.5619	92.2497	100.9840	4
		Pakistan			
1	National Bank Of Pakistan (NBP)	0.0910	9.8849	118.5053	1
2	Habib Bank Ltd (HBL)	10.4639	1.5603	1.7094	4
3	Muslim Commercial Bank Ltd (MCB)	11.9313	0.2211	0.2396	8
4	United Bank Ltd (UBL)	9.5411	1.1954	1.3207	5
5	Allied Bank Ltd (ABL)	10.8204	0.4085	0.4462	7
6	Bank Al Habib (BAHL)	7.2198	2.0889	2.3782	2
7	Meezan Bank Ltd (MBL)	6.6805	1.5204	1.7480	3
8	Askari Bank Ltd (AKBL)	10.8427	0.1425	0.1557	9
9	Bank Alfalah Ltd (BAFL)	8.4556	0.8322	0.9306	6
10	Faysal Bank Ltd (FYBL)	12.1468	0.0000	0.0000	10
		Thailand			
1	Kasikornbank PCL (KBANK)	0.3127	1409.5280	5916.4521	1
2	Bangkok Bank PCL (BBL)	117.5922	1359.9353	1371.5001	2
3	Siam Commercial Bank (SCB)	1143.2878	273.8437	274.0832	5
4	Krung Thai Bank (KTB)	1118.2005	315.1131	315.3949	4
5	TMB Bank (TMB)	616.5674	354.8573	355.4329	3
6	CIMB Thai Bank	1383.1064	0.9503	0.9509	7
7	Kiatnakin Bank (KKP)	1494.2886	0.0000	0.0000	8
8	Bank of Ayudhya	1458.6709	21.0852	21.0997	6

4.3. Grey Relational Analysis Results

Table 8 represents the results of the AHP-GRA Method. It was used to measure the performance of public and private banks in China, India, Pakistan and Thailand to identify the most successful bank in each country. The performance reviews and rankings are based on both inputs and outputs banks financial indicators. Then, a grey relational score is generated for each alternative by comparing its performance to an ideal benchmark. This grade is then used to rank the alternatives and select the best one. The banks were evaluated and ranked using a combination of the AHP-GRA methods. In the computation of GRA, the highest grey relational grade value was considered the best among others. The AHP method starts by forming a decision matrix using input and output data, then normalized through vector normalization regression. A reference sequence is then built to detect comparable sequences of various alternate solutions. The data is then normalized by equation 20 for all input and output variables. In the given study, six variables are considered, including both input and output criteria. Among these, mostly are categorised as beneficial criteria, meaning that higher values are usually preferred. Conversely, the variable "Total Liabilities" is classified as a non-beneficial standerd. For non-beneficial variables, lower values are preferable, indicating better performance. The absolute value is determined by identifying the difference between the reference sequence and the comparison series. The grey relationship coefficient matrix is determined by looking at the maximum and minimum differences between the reference sequence and the comparison series. The weight of each variable is then computed using AHP and the grey relation degree. It is calculated by dividing the sum of multiplying the criterion of the grey relational coefficient by the degree of the same criterion weight factor. The alternative with the highest degree of grey relationship is considered the best in the decision issue.

After combining AHP and GRA, Bank Of China Ltd (BOC) was found to be the most dominant alternative, with the highest degree of relation (3.3615) and grey relational grades (0.3361), and this bank is used as a benchmark for other banks. As a result, Bank Of China Ltd is considered the most successful bank among the other alternatives in the country.

Meanwhile, in the Indian banking sector, the study reported as the State Bank of India stands first in ranking with the highest degree of relation (3.7906) and highest grey relational grade points (0.3791) among other alternatives. ICICI Bank Ltd (ICBK) was found the lowest degree of relationship and the lowest grey relational levels, thus considered the lowest performing banks in the country.

Similarly, the study revealed that the National Bank of Pakistan emerged as the top performer and a benchmark for other banks in Pakistan. The Meezan Bank Ltd (MBL) demonstrated the lowest performance with a low degree of relation and grades, marking it as the worst-performing bank among the alternatives considered in the study. Kiatnakin Bank (KKP) was found the best performing bank in Thailand, while Bangkok Bank PCL (BBL) stands last. These results supported the study by Ertug and Girginer (2015) that used AHP and GRA to evaluate the commercial credit applications of private and public banking sector. Kung and Wen (2007) used GRA to analyze the financial returns of venture capitalists. Lin and Wu (2011) utilized GRA to predict the financial crisis and the financial soundness of banks.

Table 8: Calculations of grey relational grades, degree for relation, and rank

DMU#	Variables	X1	X2	X3	Y1	Y2	Y3	Degree of relation	Grades	Rank
	China									
	Weight	0.7287	0.3667	0.1437	0.2252	0.6111	0.0847			
1	Industrial and Commercial Bank of China Ltd	0.5474	0.4108	0.1013	0.5447	0.7623	0.2275	2.1601	0.2160	10
2	China Construction Bank (CCB)	0.5253	0.4180	0.0915	0.1816	0.8876	0.1774	2.5939	0.2594	5
3	Agriculture Bank of China (ABC)	0.4576	0.4553	0.0858	0.2027	1.0753	0.1522	2.2814	0.2281	9
4	Bank Of China Ltd (BOC)	0.2675	0.8638	0.0533	0.3790	1.0081	0.0960	3.3615	0.3361	1
5	China Merchants Bank Co Ltd (CMB)	0.2429	1.1000	0.0479	0.2959	1.2421	0.0760	2.6677	0.2668	4
6	Ping An Bank Co Ltd (PAB)	0.2852	0.7589	0.0553	0.2883	1.0944	0.0860	3.0048	0.3005	2
7	Bank of Communications Co Ltd (BOcom)	0.2639	0.8855	0.0514	0.2444	1.8333	0.0830	2.5681	0.2568	6
8	Industrial Bank Co Ltd (IBC)	0.2480	1.0365	0.0489	0.3025	1.1232	0.0758	2.4289	0.2429	7
9	China Everbright Bank Co Ltd (CEB)	0.2909	0.7239	0.0522	0.2374	0.9719	0.0974	2.8348	0.2835	3
10	Postal Savings Bank of China Co Ltd	0.7287	0.3667	0.1437	0.2252	0.6111	0.0847	2.3736	0.2374	8
	India									
1	State Bank of India (SBI)	0.7287	0.3667	0.1437	0.1875	1.6000	0.2275	3.7906	0.3791	1
2	HDFC Bank Ltd	0.3184	0.6594	0.0944	0.1816	1.6794	0.1022	3.0353	0.3035	8
3	ICICI Bank Ltd (ICBK)	0.2996	0.7132	0.0738	0.5447	0.6111	0.1083	2.3508	0.2351	10
4	Bank of Baroda Ltd (BOB)	0.2827	0.7720	0.0565	0.3183	1.7328	0.0845	3.2466	0.3247	7
5	Axis Bank Ltd (AXBK)	0.2738	0.8287	0.0599	0.3268	0.8458	0.0834	2.4184	0.2418	9
6	Central Bank of India Ltd (CBI)	0.2454	1.0596	0.0479	0.4840	1.8045	0.0759	3.7173	0.3717	2
7	IDBI Bank Ltd (IDBI)	0.2429	1.1000	0.0496	0.4889	1.8333	0.0758	3.2541	0.3254	6
8	Bank of India Ltd (BOI)	0.2585	0.9275	0.0512	0.3885	1.7926	0.0771	3.4955	0.3495	3
9	Union Bank of India	0.2701	0.8398	0.0524	0.3773	1.7522	0.0815	3.3732	0.3373	4
10	Punjab National Bank (PNBK	0.2792	0.7907	0.0565	0.3951	1.7583	0.0798	3.3597	0.3360	5

					Pakistan					
1	National Bank of Pakistan (NBP)	0.6498	0.3847	0.1437	0.5447	0.6111	0.1375	3.4886	0.3489	1
2	Habib Bank Ltd (HBL)	0.7287	0.3667	0.1249	0.1816	1.4423	0.2275	3.0716	0.3072	3
3	Muslim Commercial Bank Ltd (MCB)	0.3202	0.6503	0.0754	0.2020	1.7786	0.1138	3.1402	0.3140	2
4	United Bank Ltd (UBL)	0.3739	0.5438	0.0887	0.2137	1.2863	0.1161	2.6226	0.2623	6
5	Allied Bank Ltd (ABL)	0.3084	0.6724	0.0609	0.1977	1.5081	0.0905	2.8380	0.2838	5
6	Bank Al Habib (BAHL)	0.3552	0.5607	0.0633	0.3246	1.0131	0.0851	2.4020	0.2402	9
7	Meezan Bank Ltd (MBL)	0.3043	0.6747	0.0525	0.2562	0.9636	0.1137	2.3649	0.2365	10
8	Askari Bank Ltd (AKBL)	0.2610	0.8969	0.0479	0.1949	1.5090	0.0764	2.9861	0.2986	4
9	Bank Alfalah Ltd (BAFL)	0.2911	0.7298	0.0544	0.2112	1.1393	0.0892	2.5150	0.2515	7
10	Faysal Bank Ltd (FYBL)	0.2429	1.1000	0.0488	0.1877	1.8333	0.0758	2.4715	0.2472	8
					Thailand					
1	Kasikornbank PCL (KBANK)	0.6818	0.3780	0.1437	0.4399	0.6111	0.2275	3.4356	0.3436	2
2	Bangkok Bank PCL (BBL)	0.7287	0.3667	0.1328	0.3395	0.6449	0.1768	2.3894	0.2389	8
3	Siam Commercial Bank (SCB)	0.5247	0.4264	0.1144	0.2444	1.2473	0.1990	2.7562	0.2756	4
4	Krung Thai Bank (KTB)	0.5512	0.4080	0.0934	0.1816	1.2195	0.1534	2.6070	0.2607	5
5	TMB Bank (TMB)	0.3318	0.6049	0.0631	0.4638	0.8430	0.0913	2.3979	0.2398	7
6	CIMB Thai Bank	0.2454	1.0813	0.0479	0.3893	1.5959	0.0758	2.4821	0.2482	6
7	Kiatnakin Bank (KKP)	0.2429	1.1000	0.0484	0.3578	1.8333	0.0805	3.6630	0.3663	1
8	Bank of Ayudhya	0.4060	0.5011	0.0789	0.5447	1.7499	0.1431	3.4236	0.3424	3

Table 9: Rank performance comparative analysis between TOPSIS and GRA models

	China		
DMU#	DMU Name	TOPSIS Rank	GRA Rank
1	Industrial and Commercial Bank of China Ltd	8	10
2	China Construction Bank (CCB)	3	5
3	Agriculture Bank of China (ABC)	2	9
4	Bank of China Ltd (BOC)	1	1
5	China Merchants Bank Co Ltd (CMB)	7	4
6	Ping An Bank Co Ltd (PAB)	10	2
7	Bank of Communications Co Ltd (BOcom)	5	6
8	Industrial Bank Co Ltd (IBC)	4	7
9	China Everbright Bank Co Ltd (CEB)	9	3
10	Postal Savings Bank of China Co Ltd	6	8
	India		
1	State Bank of India (SBI)	1	1
2	HDFC Bank Ltd	2	8
3	ICICI Bank Ltd (ICBK)	9	10
4	Bank of Baroda Ltd (BOB)	3	7
5	Axis Bank Ltd (AXBK)	7	9
6	Central Bank of India Ltd (CBI)	8	2
7	IDBI Bank Ltd (IDBI)	10	6
8	Bank of India Ltd (BOI)	6	3
9	Union Bank of India	5	4
10	Punjab National Bank (PNBK	4	5
	Pakistan		
1	National Bank of Pakistan (NBP)	1	1
2	Habib Bank Ltd (HBL)	4	3
3	Muslim Commercial Bank Ltd (MCB)	8	2
4	United Bank Ltd (UBL)	5	6
5	Allied Bank Ltd (ABL)	7	5
6	Bank Al Habib (BAHL)	2	9
7	Meezan Bank Ltd (MBL)	3	10
8	Askari Bank Ltd (AKBL)	9	4
9	Bank Alfalah Ltd (BAFL)	6	7
10	Faysal Bank Ltd (FYBL)	10	8
	Thailand		
1	Kasikornbank PCL (KBANK)	1	2
2	Bangkok Bank PCL (BBL)	2	8
3	Siam Commercial Bank (SCB)	5	4
4	Krung Thai Bank (KTB)	4	5
5	TMB Bank (TMB)	3	7
6	CIMB Thai Bank	7	6
7	Kiatnakin Bank (KKP)	8	1
8	Bank of Ayudhya	6	3

Table 9 shows the comparision results of both AHP-TOPSIS and AHP-GRA model.

The findings from both the AHP-TOPSIS and AHP-GRA models present a comprehensive evaluation of various banks in China, India, Pakistan and Thailand. In the case of China, the combination of these methodologies resulted in Bank of China Ltd (BOC) being identified as the most dominant alternative, earning the highest degree of relation and grey relational grades. This designation positions BOC as a benchmark for other banks and suggests that it is the most successful among the alternatives in the country.

In contrast, in the case of Indian banks, the results of both models highlighted the State Bank of India as the top performer in the Indian banking sector, holding the highest degree of relation and the highest grey relational grade among other alternatives. Conversely, ICICI Bank Ltd (ICBK) was found to have the lowest degree of relationship and the lowest grey relational levels, designating it as one of the lowest-performing banks in the country. Similarly, in the context of Pakistan, the National Bank of Pakistan emerged as the top performer and a benchmark for other banks, showcasing its dominance in the local banking landscape. On the other end of the spectrum, Faysal Bank Ltd and Meezan Bank Ltd (MBL) demonstrated the lowest performance, marked by a low degree of relation and grades, designating it as the worst-performing bank among the alternatives studied. For Thailand, a small difference occurs in both model results as Kasikornbank PCL (KBANK) was identified as the second-performing bank by GRA, and ranked top by TOPSIS.

Overall, both models provide similar results and provide a comprehensive understanding of the relative performance of banks in each country, allowing stakeholders and decision-makers to identify benchmarks, strengths, and areas for improvement within their respective banking sectors. Both methods showed similar results with a slight deviation according to their ranks because of methodological differences. These results align with Sakinc (2016) that used GRA and TOPSIS to evaluate the performance of Turkish state-owned banks with different financial indicators.

5. Conclusion

In conclusion, the combined findings from the AHP-TOPSIS and AHP-GRA models offer a thorough and insightful evaluation of banks in China, India, Pakistan, and Thailand. The results underscore the robustness of both methodologies in assessing the relative performance of banks within each country. In the Chinese banking sector, the convergence of AHP-TOPSIS and AHP GRA identified Bank of China Ltd (BOC) as the most dominant alternative, positioned as a benchmark for other banks. This designation suggests BOC's superior performance among the alternatives in the country. Turning to India, both models consistently ranked the State Bank of India as the top performer, emphasizing its strong position in the Indian banking sector. In Pakistan, the National Bank of Pakistan (NBP) stood out as the top performer and a benchmark for other banks, demonstrating its dominance in the local banking landscape. In Thailand, while there was a minor difference in results between the two models for Kasikornbank PCL (KBANK), both methods agreed on its strong performance.

Overall, the combined models provided similar results, offering a comprehensive understanding of the relative performance of banks in each country. The consistency between the two models highlights their reliability, with the slight deviations in rankings attributed to methodological differences. These comprehensive assessments empower stakeholders and decision-makers to identify benchmarks, leverage strengths, and target areas for improvement within the banking sectors of the respective countries.

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