RESEARCH ARTICLE

ASIAN JOURNAL OF INTERDISCIPLINARY RESEARCH

DOI: 10.54392/ajir2521

A Multi-Criteria Decision-Making Approach to Improve Criteria Ranking and Weighting: Integrating SITDE Weighting With PIV and RAM Techniques

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DOI: https://doi.org/10.54392/ajir2521
Received: 19-02-2025; Revised: 06-04-2025; Accepted: 17-04-2025; Published: 29-04-2025

Abstract: Skewed data distributions present a major challenge to the accuracy of Multi-Criteria Decision Making (MCDM) methods in financial performance evaluation. Traditional weighting techniques often neglect skewness, leading to biased and unreliable results. This research proposed an sophisticated MCDM approach that enhances the accuracy of the criteria rankings and weighting using Skewness-Insensitive Technique for Data Evaluation (SITDE) weighting combined with Preference Index Value (PIV) and Range of Alternatives Method (RAM) methods. Global bank rankings is obtained using the PIV and RAM MCDM techniques, with final rankings derived through the Borda Count to aggregate results. The findings indicate that DBS Bank, Bank of America, and Societe Generale obtained the highest overall ranking, reflecting superior performance across the applied techniques. By addressing data skewness and enhancing the robustness of the evaluation process, this approach offers a more accurate and adaptive solution for financial decision-making. The integration of SITDE weighting with PIV and RAM represents a meaningful advancement in the application of MCDM methods for global bank performance assessment.

Keywords: Multi-Criteria Decision Making (MCDM), SITDE Weighting, Preference Index Value (PIV), Range of Alternatives Method (RAM), Global Bank Ranking, Financial Performance Evaluation

1. Introduction

Global banks are essential for assessing the financial health, stability, and performance of banks in an increasingly interconnected global economy. Financial performance evaluation involves analyzing key metrics such as profitability, solvency, risk management, and operational efficiency to provide a comprehensive assessment of a bank's resilience and market position. In the world's global financial structure, the identification of accurate ranking of banks and categorizing them in terms of their financial stability, performance, and solace has posed a significant challenge for bank regulators, investors, and other stakeholders (Biswas et al., 2025). Integration of various financial systems, risk and return dependencies, market fluctuations, and constantly changing regulatory environments point toward a proper approach to ranking methodologies (Saunders et al., 2021). Banks are not ranked on return on equity but are measured on their solvency, soundness, operations, risk control, and shareholders' satisfaction. In combination, these criteria define a bank's financial stability, as well as economic changes, crises, and competition pressure (Komatina et al., 2026). Moreover, the integration of diverse financial systems, varying risk-return dependencies, and the constant evolution of market conditions and regulatory environments underscore the need for a more comprehensive approach to ranking methodologies (Saunders et al., 2021). For instance, the recent regulatory changes, such as the implementation of Basel III, have forced banks to hold higher capital reserves, yet traditional ranking methods may not fully capture the impact of these evolving regulations. A key issue with existing methods is their failure to account for skewed data distributions within financial metrics, leading to biased and misleading rankings. For example, In 2015, Deutsche bank ranked lower in terms of profitability but had significant hidden risks related to derivatives exposure, which were not captured in standard ranking models. As a result, there is a pressing need for an improved framework that not only considers these complex factors but also addresses the impact of skewness on ranking accuracy, ensuring more reliable and meaningful evaluations of bank performance.

Over the past several years, using Multi Criteria Decision-Making (MCDM) tools to rank and evaluate has received increasing attention. Unlike the conventional single-measure models, MCDM techniques make evaluating performance from different perspectives possible using versatile financial criteria (Yalçın et al., 2025). This approach is especially relevant for the banking industry, where it is impossible to quantify financial performance through a single indicator. The high dynamics of financial products forecast such a requirement, the rising requirements for non-financial reporting, and the shift toward sustainable and responsible banking (Sama et al., 2023). This research endeavor is inspired by the shortcomings of applying conventional ranking models, which may not consider some critical aspects of the operation and risk management of the banking institution. For instance, MCDM methodologies, the Root Assessment Method (RAM) and Preference Index Value (PIV) approach, the present work tends to offer a multi-criterion ranking system, which will include a broad set of performance criteria to evaluate the banks under analysis. It also allows one to perform more balanced comparisons between the institutions and helps the stakeholders to make better decisions concerning the stability and risk management of banks (Nalluri et al., 2024). In doing so, this study warrants the current gap in the literature by proposing credible composite ranking systems for global banking structures to enhance financial system resiliency and credibility (Beck et al., 2018).

Standard approaches to ranking found in MCDM literature are not well suited when applied to such financial data primarily because many of them cannot handle skewed distributions appropriately. Most traditional techniques, like Analytic Hierarchy Process (AHP) and entropy-based models, consider the data uniformly distributed. In contrast, the data is often skewed in real-life scenarios, especially regarding characteristics like asset size, profitability operation cost, etc. Biswas et al., 2025 & Gopisetty and Sama, 2024 oversight incurs bias in ranking and distorts each bank's actual status of Solvency out of the two. For instance, some banks with very high values or shallow values in some of the metrics may need to be more emphasized or under-emphasized, thus painting a wrong picture of the firms' performance and risk characteristics (Nalluri et al., 2024). Traditional approaches add to the problem because they are rigid in their application. Many current models need to consider the differences in the statistical distribution of each assessment criterion, assigning equal weight to every criterion or assigning weights that do not change as the data characteristics do. This restriction is especially disturbing in complex monetary settings where criteria typically have such asymmetry and extremes significant for discerning authentic bank efficiency (Beck et al., 2018). The problem of distorted weights is solved in the framework of more refined weighting methods, including Skewness Impact through Distributional Evaluation (SITDE), which adapts weights to the distributional characteristics of the criteria – Skewness and entropy. With the help of SITDE, it becomes possible to apply balanced and context-oriented weighting, which helps to tone down criteria with higher Skewness, which in turn increases the reliability of the rankings (Gopisetty and Sama, 2024; Okwoma 2012).

Although SITDE can capture the skewed data characteristics of the problem, the literature reveals that its application in conjunction with MCDM techniques is still being determined. SITDE is suggested to be integrated with another multi-criteria decision-making technique, such as the RAM or PIV among others, to manufacture a more complex and realistic assessment of the competence of banks. When applied, the integration can enhance the reliability of the rankings, mainly because each financial criterion possesses distinct distributional properties and must reflect specific relevant data sensitivity. The current study aims to fill this gap by developing an MCDM framework comprising SITDE, which provides more accurate coverage than simple rankings of banks and offers the reader a clearer insight into the prospects and risks of the banking sector's financial health. The purpose of this research is threefold: to introduce a new ranking approach for global banks; to assign the SITDE weighting method combined with PIV and RAM when constructing the global ranking for banks; and to undertake the integration of the proposed approach within the framework of MCDM.

The first goal is to overcome the drawbacks of comparative analysis and evaluate companies based on their financial ratios using SITDE skewness-sensitive weights, which consider asymmetry in their distributions. As for PIV and RAM combined with SITDE, this approach enhances the ranking model by employing additional aspects of bank performance metrics, including their scale and distribution characteristics. This coordinated research approach aims to allow the interested parties to obtain a more refined instrument for assessing the financial soundness, operational solidity, and relative standing of a broad cross-section of international banks to achieve a more realistic and equitable assessment of the risk and competitiveness profiles within the banking industry. The current study proposes a new model of bank ranking, employing SITDE weighting, PIV, and RAM integrated with the MCDM method. Thus, this study's hybrid approach constitute a subtle and data-oriented evaluation method that is helpful for decision-makers in banking and finance. Even when decision-makers interpret skewed statistics, the approach counteracts data asymmetry to improve ranking precision and eliminate distortions in standard assessments. This ranking model is helpful in strategic planning by giving an overview of any bank's critical aspects and thus assists in risk management and competitive analysis. Furthermore, this research fills up the gap relating to the utilization of SITDE with MCDM techniques to explore areas in more complicated financial structures within the studies about financial evaluation methods.

2. Literature review

Multi-Criteria Decision-Making (MCDM) methods have become indispensable tools for addressing complex decision problems involving multiple, often conflicting, criteria. These techniques are widely applied across fields such as engineering, sustainability, finance, healthcare, logistics, and public policy, offering systematic approaches for evaluating alternatives and supporting informed decisions (Hussain et al., 2024). A fundamental process in any MCDM approach is the determination of criteria weights, which significantly influences the outcome of the decision model. Various methods have been developed for this purpose, including both subjective approaches, such as the AHP (Yalçın et al., 2025), Best-Worst Method (Biswas et al., 2025), and Analytic Network Process (ANP), and objective approaches, such as the Criteria Importance Through Intercriteria Correlation (CRITIC) (Gopisetty and Sama, 2024), Entropy (Saunders et al., 2021), and Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Nalluri and Chen, 2022). Most importantly, the applied MCDM model has highlighted the importance of using fuzzy logic to handle unavoidable uncertainties. Wu et al., 2009 further developed this concept and used the Fuzzy MCDM with the balance scorecard to show that it is possible to perform a satisfying integration of both qualitative and quantitative criteria. Hence, such methods underscore the significance of an adaptable decision model as proposed in SITDE weighting schemes.

Other MCDM techniques have also been used to increase the depth of evaluation. A proposed efficiency ranking method called ERM-DT DEA and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) combined method for Indian banks shows that efficiency analysis can complement ranking techniques such as TOPSIS. While subjective methods are valued for incorporating expert judgment, they are often criticized for bias and inconsistency. Objective methods like CRITIC and Entropy have been introduced to address these issues by using quantitative data to derive criteria weights. CRITIC, in particular, considers both the standard deviation of each criterion and the degree of correlation between criteria, offering a balanced approach to reflect criteria contrast and conflict. In their study, Liu et al., 2016 applied the CRITIC-Multi-Attributive Border Approximation Area Comparison (MABAC) hybrid approach to evaluate the financial performance of companies listed in the Borsa Istanbul Sustainability Index. By employing CRITIC for weight assignment and MABAC for ranking, the study illustrated the effectiveness of combining objective and compensatory decision models. The literature surveyed in their work also confirmed the growing popularity of integrated models using methods like TOPSIS, VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS), and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) in diverse industries such as banking, retail, energy, and manufacturing (Abdel-Basset et al., 2021; Maredza et al., 2022; Singh and Singla, 2016; Rawat et al., 2022; Stanujkic et al., 2013). In addition, Wanke et al., 2022 used the MCDM/z-numbers approach to investigate ASEAN banks. Whereas, Boubaker et al., 2024 applied the CAMELS coupled with Shannon entropy to develop an integrated index for bank stability; stressing on the amalgamation of complicated, integrated systems in decision-making. Pekkaya and Erol, 2019 have indirectly supported the work done here by proposing the prioritization of CAMELS dimensions for performance evaluation, emphasizing the need for highly detailed criteria-based assessments to achieve SITDE's objective of dynamic weighting.

Another stream of MCDM development focuses on improving ranking techniques. For example, Pekkaya and Erol, 2019 proposed the RADAR and RADAR II methods, which utilize a dual normalization system to evaluate alternatives based on their distance from ideal and anti-ideal solutions. Their method demonstrated strong mathematical properties such as consistency and monotonicity and was applied to industrial decision contexts such as equipment selection and failure mode prioritization. Nevertheless, RADAR does not include an internal mechanism for dynamic or data-driven weight estimation, reinforcing the need for more comprehensive frameworks that combine ranking and weighting in a unified structure (Mohan and Irfan, 2024). Hybrid models that integrate multiple methods have gained attention due to their potential to leverage the strengths of different approaches. For instance, combinations like AHP-TOPSIS, DEMATEL-ANP, and CRITIC-MARCOS have been used effectively in applications ranging from healthcare resource allocation to sustainable supplier selection (Roy and Shaw, 2023; Nalluri et al., 2025). However, many of these models are limited by their reliance on linear normalization techniques and static weights. In this context, integrating the SITDE weighting technique with PIV and RAM represents a significant methodological advancement (Wanke et al., 2016). SITDE incorporates stochastic modeling of inter-criteria influence, tendency, and dependency, offering a more adaptive and context-sensitive weighting scheme. Meanwhile, PIV and RAM enhance the ranking process by capturing relational assessments and proximity effects between alternatives. Together, this integration offers a powerful and flexible framework for complex decision-making scenarios, where both the importance of criteria and the ranking of alternatives must be treated dynamically and with greater sensitivity to uncertainty. Therefore, the integration of SITDE weighting with PIV and RAM continues the development of these improvements to provide a flexible, resilient decision-making tool to address the diverse and increasingly complicated global bank performance assessments.

3. Methodology

3.1 Data collection

In this regard, data collection in this study is focused on obtaining relevant financial factors of a group of global banks to carry out an MCDM study. Table 1 presents an overview of the selected banks, The Bank codes by which they will be identified further, and some essential financial indicators that will be used as primary criteria. Each reflects a particular characteristic of bank performance and allows for a comprehensive analysis of each institution, considering all the critical aspects of the bank's activities. The data used in the analysis was collected from the PROWESS database (https://prowessiq.cmie.com/).

Table 1. Bank abbreviations and key financial metrics for multi-criteria decision-making

Criteria		Alternatives	
Bank name	**Bank code**	**Financial meric**	**Metric code**
Standard Chartered Bank	SCB	BORROWINGS	BORR
CITI Bank	CITI	OPERATING EXPENSES	OPEXP
HSBC	HSBC	TOTAL ASSETS	TOTAST
Bank of America	BoA	DEPOSITS	DEPO
Deutsche Bank	DB	NET PROFIT	NPROF
Barclays Bank	Barclays	CASH	CASH
BNP Paribas	BNP	INVESTMENT	INVST
Bank of Tokyo	BOT	ADVANCES	ADV
Societe Generale	SG		
DBS Bank	DBS		
Credit Suisse	CS		

Table 2. Financial metrics for global bank analysis and their significance

Metric	Description	Significance
Borrowings	Total external funding is sourced through debt.	Indicates financial leverage and risk exposure; higher borrowings suggest reliance on debt for funding, which can increase financial risk.
Operating expenses	Day-to-day operational costs, including salaries, utilities, and rent.	Reflects cost efficiency and operational scale; lower expenses indicate effective cost management, while higher expenses may suggest inefficiencies.
Total assets	The total value of the bank's assets, including cash, investments, loans, and property.	Measures the bank's size and market reach; larger assets imply stronger market position but also greater responsibilities and risks.
Deposits	Customer funds entrusted to the bank in savings and checking accounts.	Indicator of customer trust and funding stability; higher deposits provide a stable source of funds for lending and investment activities.
Net profit	Profit after all expenses, taxes, and costs have been deducted from revenue.	Key measure of financial performance; higher net profits indicate robust financial health and efficiency, while lower profits may signal challenges.
Cash	Liquid assets available for meeting immediate obligations and day-to-day operations.	Reflects liquidity and short-term financial resilience; essential for handling sudden demands but may also indicate missed investment opportunities if excessive.
Investment	Funds allocated to financial instruments, such as bonds, stocks, and securities, to generate returns.	Provides insight into risk-return profile and strategic asset allocation; high investments suggest active risk-taking and income generation.
Advances	Loans and credit facilities extended by the bank to individuals or businesses.	Measures lending activity and income potential through interest; high advances reflect an aggressive lending strategy but increase credit risk exposure.

A brief on critical financial ratios often employed in assessing the performance and solidity of global banks within an MCDM environment is presented in Table 2 below. Every figure informs various aspects of the bank business, including financial health, Solvency, revenue, and vulnerability. These metrics are beneficial to create an overall and sound analysis, which is necessary for constructing the most effective and sound ranking system covering top international banks.

3.2 Applying SITDE weighting

In this section we discussed objective weighing method SITDE Gopisetty and Sama, 2024 is designed to address limitations in traditional MCDM approaches by incorporating Skewness as a critical factor in evaluating and weighting criteria. The following is the algorithm:

Step 1: Develop the evaluation matrix. In this phase, construct a scoring matrix X_{ij} representing the scores of each option relative to each factor, ensuring all values are positive ($X_{ij} > 0$). For n options and m factors, any negative values should be converted to positive using an appropriate method.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Step 2: Normalize the decision matrix (X). In this stage, apply basic linear normalization to scale the values in the decision matrix uniformly. The elements in the normalized matrix are denoted as Z_{ij}^{x}. Here, J represents the set of beneficial criteria, and H indicates the set of non-beneficial criteria. The normalization process follows these formulas.

$$Z_{ij}^{x} = \begin{cases} \frac{\min S_{kj}}{S_{ij}} & if \quad j \in \text{J} \\ \frac{S_{ij}}{\max S_{kj}} & if \quad j \in \text{H} \end{cases} \tag{2}$$

While normalization techniques are similar to those in methods like Weighted Aggregated Sum Product Assessment (WASPAS), this approach differs by alternating between beneficial and non-beneficial criteria formulas, with all criteria uniquely transformed into minimization type standards.

Step 3: In this step, we calculate the Skewness for each criterion using the normalized scores from step 1, providing insight into the asymmetry of the distribution of scores for each criterion.

$$K_j = \frac{N}{(N-1)(N-2)} \sum_{i=1}^{N} \left(\frac{Z_{ij}^{x} - \overline{Z_j}}{\sigma_j} \right)^3 \tag{3}$$

Here,

K_j symbolizes the asymmetry measure, or Skewness, associated with criterion j.

N stands for the aggregate count of alternatives evaluated.

Z_{ij} signifies the adjusted scores for each option i concerning criterion j.

Z_j represents the average value derived from the adjusted scores pertinent to criterion j.

σ_j is the standard deviation of the normalized scores for criterion j.

Step 4: In this step, the skewness values derived from the distributions of various criteria are normalized through the following transformation:

$$LK_j = log\left|\left((K_j + 1) + \left(\left|min(K_j)\right| + 1\right)\right)\right| \tag{4}$$

Here,

LK_j represents the normalized Skewness for the j^{th} criterion.

K_j is the original skewness value for the j^{th} criterion.

The expression $\left(\left|min(K_j)\right| + 1\right)$ ensures all values inside the logarithmic function are positive by offsetting with the smallest skewness value among all criteria, incremented by one.

Step 5: Determine the final weights for each criterion by adjusting them according to the respective normalized skewness values to reflect their influence accurately.

$$W_j = \frac{LS_j}{\sum_{k=1}^{m} LS_k} \tag{5}$$

Here,

W_j represents the determined weight for the j^{th} criterion.

LS_j stands for the normalized Skewness of the j^{th} criterion.

m indicates the total count of criteria involved.

The denominator, $\sum_{k=1}^{m} LS_k$, is the total of all criteria's normalized skewness values, ensuring that each determined weight, W_j, proportionally reflects the criterion's distributional characteristics within the collective decision framework.

3.4 PIV and RAM techniques

3.4.1 Preference Index Value (PIV)

Mufazzal and Muzakkir 2018 was used the PIV method is widely applicable across various fields that require complex decision-making based on multiple criteria. Here are some key application areas: selection of a green renewable energy source (Calikoglu and Luczak, 2024), transmission rod material selection (Thinh and Mai, 2023), selection of plastic injection moulding machines (Dudic et al., 2024) and selection of an additive manufacturing process (Raigar et al., 2020). The experimental matrix was generated as equation (1). The steps for implementation of multi-criteria decision- making according to the PIV method are as follows:

Step 1: Determine the normalized decision matrix.

$$y_{ij}^{'} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} y_{ij}^{2}}} \tag{6}$$

Step 2: Describe normalized values

$$Y = w_j . y_{ij}^{\prime} \tag{7}$$

where, W_j is the weight of the criterion j.

Step 3: Determine the weighted proximity value for each alternative.

$$u_i = \begin{cases} Y_{\max} - Y_i & for\ C_{1,} C_2, \ldots\ldots\ldots, C_n \in B \\ Y_i - Y_{\min} & for\ C_{1,} C_2, \ldots\ldots\ldots, C_n \in C \end{cases} \tag{8}$$

where B represents the max criterion, and C represents the min criterion.

Step 4: Determine the overall proximity value.

$$d_i = \sum_{j=1}^{n} u_i . \tag{9}$$

Step 5: Ranking the options according to the rule that the alternative with the shortest of di is considered the best.

3.4.2 Root Assessment Method (RAM)

AR and VR are transforming the learning experience, especially in STEM education, where experiential This covered a recently developed ranking method (Sotoudeh-Anvari 2023). This method has been applied to the following areas: sustainability challenges (Sotoudeh-Anvari 2023), forest fire detection and management (Mohamed et al., 2024a), sustainable transportation (Elsayed 2024), and traffic safety in the Metaverse (Mohaned et al., 2024b). Below are the steps for the RAM method. In an MCDM problem, a finite set of m alternatives is ranked based on n criteria. These criteria are categorized into beneficial criteria (e.g., profit and efficiency, where higher values are preferable) and non-beneficial criteria (e.g., price and risk, where lower values are preferable). Representing the value of the i^{th} option for the j^{th} criterion, a decision matrix of m alternatives and n criteria can be constructed as follows:

$$D = \begin{bmatrix} x_{11} & x_{12} & \ldots\ldots\ldots & x_{1n} \\ x_{21} & x_{22} & \ldots\ldots\ldots & x_{2n} \\ . & .. & . & .. \\ x_{m1} & x_{m2} & \ldots\ldots\ldots & x_{mn} \end{bmatrix} \qquad W = [w_1, w_2, \ldots\ldots, w_n] \tag{10}$$

Step 1: Normalize the decision matrix using a linear sum normalization formula to standardize the values across the matrix

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad (j = 1,2,\ldots,n) \tag{11}$$

Step 2: Compute the weighted normalized decision matrix by applying:

$$y_{ij} = r_{ij} w_j \qquad (i = 1,2,\ldots, m; \ j = 1,2,\ldots, n) \tag{12}$$

Step 3: Calculate the total weighted normalized scores for both beneficial and non-beneficial criteria for each alternative using the following equations:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \tag{13}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \tag{14}$$

In the above equations, S_{+i} is the sum of weighted normalized values of beneficial criteria and S_{-i} is the sum of weighted normalized values of the non-beneficial criteria.

Step 4: Compute the overall score for each alternative using the following aggregation function:

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \qquad (i = 1,2,\ldots, m) \tag{15}$$

4. Results of this study

4.1 Financial data summary

The dataset summarized in Table 3 provides key financial indicators for a selection of global banks, serving as the empirical foundation for the MCDM analysis. These indicators, including borrowings, operating expenses, total assets, deposits, net profit, cash, investment, and advances, each capture specific dimensions of bank performance, ranging from risk exposure and operational scale to profitability and liquidity. Borrowings, for instance, reveal banks' reliance on external funding, with CITI bank reporting the highest level (345,700) and Societe Generale the lowest (2,633), suggesting varied funding strategies across institutions. Similarly, operating expenses vary widely, with standard chartered banks (84,214) reflecting a larger operational footprint compared to the lower cost base of Bank of America (3,861). Total assets, serving as a proxy for market presence, highlight Bank of America's substantial influence (5,032,500) in contrast to the comparatively modest assets of Credit Suisse (452,507). Deposits indicate customer trust and funding stability, where Bank of America and Standard Chartered Bank lead with 1,923,827 and 1,440,856, respectively, while Credit Suisse holds one of the most miniature deposit bases (203,427).

Net profit levels demonstrate operational efficiency, with DBS Bank achieving the highest profit (50,213) and Bank of America the lowest (2,853), reflecting differences in revenue generation and cost management. Cash reserves, a measure of liquidity, show Barclays Bank and Societe Generale holding significant amounts (224,634 and 241,997), enhancing their capacity to meet short-term obligations. In contrast, DBS Bank's cash holdings are more constrained (10,063). Investments represent each bank's risk-return profile, with BNP Paribas and Societe Generale allocating the most (452,220 and 455,438), contrasting with Credit Suisse's conservative approach (9,536). Advances, which reflect lending activity, are high for Bank of America (1,053,732) and Standard Chartered bank (870,762), while Societe Generale and Credit Suisse exhibit smaller loan portfolios (9,610 and 39,114).

The diversity in these financial indicators underscores significant differences in strategic focus and financial resilience among banks, making them ideal for the SITDE-weighted PIV and RAM approaches in MCDM. By applying the skewness-adjusted weights on these metrics, the analysis seeks to extend the evidence of the asymmetry of financial data and produce a relative measure of the firm's profitability ranking by capital risk and stability. This approach, which captures most operational and financial performance dimensions of these global banks, is aimed at offering a more balanced and insightful ranking that more stakeholders, such as investors and the regulating authorities, can use to understand the state of health and competitive strategy of these banking institutions.

4.2 Measurement of weights using the SITDE weighting method

This part of the document outlines how to determine weights on the financial criteria of global banks using the SITDE weighting method. It also proves useful for predicting metrics with asymmetric distributions in which more emphasis is placed on the variability of criteria. What is sought is a credible and harmonized assumption that will justify quantification by fairly depicting the distributional attributes of each measure. Table 4 depicts the normalized scores for the financial criteria of global banks.

Table 3. Financial indicators of global banks for multi-criteria decision-making analysis.

BANKS	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	211833	84214	2373010	1440856	37298	86113	1100508	870762
CITI	345700	56366	2411834	233590	13614	27342	519085	671217
HSBC	43638	32070	3038677	73163	24599	22814	159478	27354
BoA	32098	3861	5032500	1923827	2853	25789	0	1053732
DB	9600	16391	1312331	622035	4999	184556	251856	473705
Barclays	41601	16931	1477487	538789	4274	224634	256836	399496
BNP	22192	30956	2591499	95175	10298	288259	452220	32616
BOT	15937	4628	370409	188800	5084	37314	75026	173682
SG	2633	16849	1554045	541677	3920	241997	455438	9610
DBS	11567	8291	739301	535103	50213	10063	20997	416613
CS	47637	22122	452507	203427	4114	124966	9536	39114

Table 4. Normalized scores for financial criteria of global banks.

Bank	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	0.27	0.288	0.111	0.225	0.231	0.068	0.333	0.209
CITI	0.441	0.193	0.113	0.037	0.084	0.021	0.157	0.161
HSBC	0.056	0.11	0.142	0.011	0.153	0.018	0.048	0.007
BoA	0.041	0.013	0.236	0.301	0.018	0.02	0	0.253
DB	0.012	0.056	0.061	0.097	0.031	0.145	0.076	0.114
Barclays	0.053	0.058	0.069	0.084	0.027	0.176	0.078	0.096
BNP	0.028	0.106	0.121	0.015	0.064	0.226	0.137	0.008
BOT	0.02	0.016	0.017	0.03	0.032	0.029	0.023	0.042
SG	0.003	0.058	0.073	0.085	0.024	0.19	0.138	0.002
DBS	0.015	0.028	0.035	0.084	0.311	0.008	0.006	0.1
CS	0.061	0.076	0.021	0.032	0.026	0.098	0.003	0.009

It is used to compare the relative values of the above-mentioned financial ratios of selected banks based on certain norms, eliminating fluctuation due to differences in size and operations. Equation (2) is applied to determine the normalized scores. These normalized values range between 0 and 1, where the above score is typical of high relative performance for this metric.

The Skewness calculation for normalized financial criteria is presented in Table 5 using equation (3). Skewness measures the asymmetry of each metric distribution and highlights the presence of outliers. High skewness values, such as those observed in borrowings (2.1668) and operating expenses (1.5875), indicate metrics with significant variability among banks.

Normalized Skewness values for financial criteria are presented in Table 6 using equation (4). By normalizing Skewness values, the analysis standardizes the effect of asymmetry across all metrics, ensuring consistent comparisons. For instance, borrowings and deposits have normalized Skewness values of 1.551 and 1.421, respectively, indicating that these metrics contain significant outliers even after initial normalization. Normalized Skewness values are crucial for fair weighting in the SITDE approach, as they allow each metrics influence to be adjusted relative to its degree of asymmetry.

Table 5. Skewness calculation for normalized financial scores.

Criteria	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
Skewness	2.1668	1.5875	1.0705	1.591	1.5113	0.5484	1.5622	0.677

Table 6. Normalized Skewness values for financial criteria.

Criteria	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
Normalized Skewness	1.551	1.42	1.286	1.421	1.401	1.13	1.414	1.171

Using equation (5). These weights are used to rank the alternatives in MCDM ranking methods. These weights are normalized Skewness using high asymmetrical metric values and achieve low values for low asymmetrical values. For instance, since skews are higher for Borrowings, Operating Expenses, and Deposits, weights of 0.13 and above are assigned to capture higher weightage in the ranking. Therefore, the cash (0.10) and advances (0.11) with lower Skewness are proportionately less influenced. This weighting methodology makes it possible to have fair weighing and ranking because the factors that have significant variances are given balanced scores.

Table 7. Criteria weights based on normalized Skewness values.

Criteria	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
Weights	0.14	0.13	0.12	0.13	0.13	0.1	0.13	0.11

4.3 Ranking using the PIV MCDM method

Here, with the help of inventiveness strategy of MCDM from the PIV model, we compare the ranking of global banks and assess the level of their deviation from the optimal indicators of their financial performance.

Table 8. Normalized matrix of financial criteria for global banks.

BANK	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	0.27	0.288	0.111	0.225	0.231	0.068	0.333	0.209
CITI	0.441	0.193	0.113	0.037	0.084	0.021	0.157	0.161
HSBC	0.056	0.11	0.142	0.011	0.153	0.018	0.048	0.007
BoA	0.041	0.013	0.236	0.301	0.018	0.02	0	0.253
DB	0.012	0.056	0.061	0.097	0.031	0.145	0.076	0.114
Barclays	0.053	0.058	0.069	0.084	0.027	0.176	0.078	0.096
BNP	0.028	0.106	0.121	0.015	0.064	0.226	0.137	0.008
BOT	0.02	0.016	0.017	0.03	0.032	0.029	0.023	0.042
SG	0.003	0.058	0.073	0.085	0.024	0.19	0.138	0.002
DBS	0.015	0.028	0.035	0.084	0.311	0.008	0.006	0.1
CS	0.061	0.076	0.021	0.032	0.026	0.098	0.003	0.009

Table 9. Weighted normalized values for financial criteria of global banks.

BANK	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	30436.6	11077.2	282774.6	189637.1	4841.7	9018.3	144130	94476.9
CITI	49670.8	7414.2	287401	30743.8	1767.3	2863.4	67982.9	72826.4
HSBC	6270	4218.4	362097.3	9629.3	3193.2	2389.2	20886.3	2967.9
BoA	4611.9	507.9	599686.9	253203	370.4	2700.8	0	114329
DB	1379.3	2156	156381.1	81868.7	648.9	19328	32984.8	51396.5
Barclays	5977.3	2227	176061.5	70912.3	554.8	23525.2	33637	43344.9
BNP	3188.6	4071.8	308810.4	12526.4	1336.8	30188.5	59225.8	3538.8
BOT	2289.9	608.8	44139	24848.8	660	3907.8	9825.9	18844.3
SG	378.3	2216.3	185184.4	71292.4	508.9	25343.6	59647.3	1042.7
DBS	1662	1090.6	88097.2	70427.2	6518.2	1053.9	2749.9	45202.1
CS	6844.6	2909.8	53922	26773.9	534	13087.3	1248.9	4243.8

The weighted normalized scores are calculated using equation (7) and presented in Table 9. To determine relative importance of each metric, skewness-adjusted factors were used to obtain weights for each of the normalized scores obtained in the previous analysis.

The values for each criterion, derived from the distance from the ideal and anti-ideal solutions, are presented in Table 10 using equation (8). Here, the weighted normalized scores were compared with the ideal and anti-ideal weights for each criterion in the case of each bank. This proximity measurement allows for the evaluation of the relative distance of each bank to the ideal performance level. It provides criteria to differentiate how close an institution is to the perfect predetermined criteria values. These proximity scores are mainly beneficial for defining each bank's position relative to these two types – both higher and lower performers.

Table 10. Proximity to ideal and anti-ideal values for each criterion.

Bank	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	30058.3	10569.3	316912.4	63565.9	1676.5	21170.1	0	19852.1
CITI	49292.5	6906.3	312286	222459.2	4751	27325	76147.1	41502.5
HSBC	5891.7	3710.5	237589.6	243573.7	3325	27799.2	123243.7	111361
BoA	4233.6	0	0	0	6147.9	27487.7	144130	0
DB	1001	1648.2	443305.9	171334.3	5869.3	10860.5	111145.3	62932.4
Barclays	5599	1719.2	423625.4	182290.7	5963.4	6663.2	110493	70984
BNP	2810.3	3564	290876.6	240676.6	5181.4	0	84904.2	110790
BOT	1911.5	100.9	555548	228354.2	5858.3	26280.7	134304.1	95484.6
SG	0	1708.4	414502.5	181910.6	6009.4	4844.9	84482.8	113286
DBS	1283.7	712.3	87718.9	70048.9	6139.9	675.6	2371.6	44823.8
CS	6466.261	2531.533	53543.7	26395.57	155.7317	12708.98	870.5851	3865.52

Table 11 shows the overall proximity values and final rank of the banks tested in this study. This table calculates distance to the best for all criteria simultaneously, which gave the overall distance from the best for each bank using equation (9).

Table 11. Overall proximity values and ranking of global banks.

Bark	Overall proximity value	Rank
SCB	463804.5	4
CITI	740669.7	6
HSBC	756494.5	7
BoA	181999.2	2
DB	808096.8	10
Barclays	807338	9
BNP	738803.2	5
BOT	1047842	11
SG	806744.8	8
DBS	213774.5	3
CS	106537.9	1

Widely used global banks are presented in Table 11 in terms of the online PIV method that measures distances from the benchmarked ideal of performance about the selected financial. The PIV method is a suitable mechanism for comparing the banks given that the group assesses the various functions of the bank from the stability, resilience, and degree of financial efficiency regarding the other. The results from the PIV ranking show that Credit Suisse (CS) is the most-ranked bank among all the top positions holding the first position.

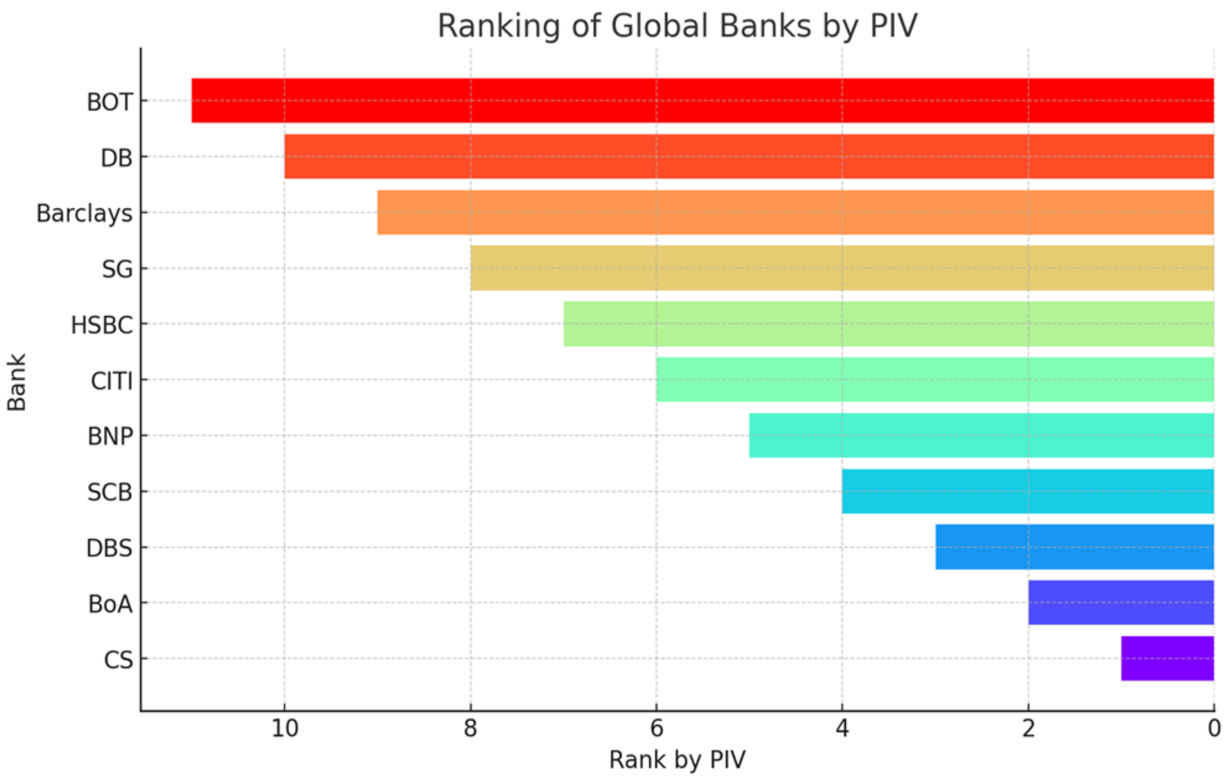

Figure 1. Ranking of global banks by PIV.

This means CS is virtually in synch with the best performance benchmark, implying a solid trend of financial Solvency and performance optimized for the parameters used in this research. Bank of America (BoA) and DBS Bank (DBS) follow this. It is assumed that high rankings mean these institutions possess good financial stability and relatively sustainable financial performance in the analyzed indicators. The fourth and fifth-ranked banks are Standard Chartered Bank (SCB) and BNP Paribas (BNP). Although they perform competitively, this reveals that they could be slightly lacking in areas compared to other higher-ranked banks. BNP Paribas is placed in the upper-middle position, which means it has a strong financial status for inhabitants but could be more correlated with the ideal scores by particular adjustment. On the other hand, Bank of Tokyo (BOT) and Db – Deutsche Bank (DB) are ranked the 11th and the 10th large forex banks individually. The PI is ranked lower in these banks, suggesting that they are, in some way, less optimal to the desired PIV method's performance criteria and, therefore, might be facing some difficulty in attaining the best financial performance in some of its benchmarks. Barclays and HSBC are also located at the lower-middle range, expecting ninth and seventh positions, respectively, meaning moderate fit with the ideal performance and probable favorable areas for strategic changes.

The ranking method of PIV (Figure 1) consequently provides a broad approach to identifying global banks' positions based on financial strength and vulnerability. CS, BoA, and DBS are high-ranking banks that all conform to the benchmark of perfect performance in a competitive environment. On the other hand, the less-ranked banks, such as BOT and DB, could profit from specific initiatives to develop some aspects of finance, such as profitability or liquidity. This ranking is also essential for several stakeholders, who could use it to determine which institutions might offer less risky or more viable opportunities in international banking. In addition, these findings support using the PIV method to differentiate the financial condition of banks and prove its efficiency for application at the stages of MCDM in the financial industry.

4.4 Ranking using the RAM MCDM method

This section evaluates the international banks for ranking using the RAM MCDM technique. The RAM method assesses each bank's scores against several financial parameters. RAM involves standardizing financial scores and then applying weights to those criteria to prioritize them. To the obtained weighted normalized scores, the following proximity expressions are then applied to quantify each bank's beneficial (desirable) and non-beneficial (undesirable) performances. Table 12 provides the normalized financial scores of the global banks to be used as basic raw data in the RAM-MCDM analysis using Equation (11). This normalization helps create a fair measure for each criterion, allowing subsequent weighted comparisons across the banks regardless of their size or structure.

Table 12. Normalized financial scores of global banks using RAM-MCDM.

Criteria	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	0.27	0.288	0.111	0.225	0.231	0.068	0.333	0.209
CITI	0.441	0.193	0.113	0.037	0.084	0.021	0.157	0.161
HSBC	0.056	0.11	0.142	0.011	0.153	0.018	0.048	0.007
BoA	0.041	0.013	0.236	0.301	0.018	0.02	0	0.253
DB	0.012	0.056	0.061	0.097	0.031	0.145	0.076	0.114
Barclays	0.053	0.058	0.069	0.084	0.027	0.176	0.078	0.096
BNP	0.028	0.106	0.121	0.015	0.064	0.226	0.137	0.008
BOT	0.02	0.016	0.017	0.03	0.032	0.029	0.023	0.042
SG	0.003	0.058	0.073	0.085	0.024	0.19	0.138	0.002
DBS	0.015	0.028	0.035	0.084	0.311	0.008	0.006	0.1
CS	0.061	0.076	0.021	0.032	0.026	0.098	0.003	0.009

The weighted normalized decision matrix is presented in Table 13 using Equation (12). Each score from the normalized matrix in Table 12 has been multiplied by its corresponding weight, adjusted to capture the importance of each criterion within the analysis. This weighting process reflects the influence of each financial metric on the RAM ranking, emphasizing the criteria deemed most critical.

Table 13. Weighted normalized decision matrix for financial criteria.

Criteria	BORR	OPEXP	TOTAST	DEPO	NPROF	CASH	INVST	ADV
SCB	30436.6	11077.2	282774.6	189637.1	4841.7	9018.3	144130.0	94476.9
CITI	49670.8	7414.2	287401.0	30743.8	1767.3	2863.4	67982.9	72826.4
HSBC	6270.0	4218.4	362097.3	9629.3	3193.2	2389.2	20886.3	2967.9
BoA	4611.9	507.9	599686.9	253203.0	370.4	2700.8	0.0	114328.9
DB	1379.3	2156.0	156381.1	81868.7	648.9	19328.0	32984.8	51396.5
Barclays	5977.3	2227.0	176061.5	70912.3	554.8	23525.2	33637.0	43344.9
BNP	3188.6	4071.8	308810.4	12526.4	1336.8	30188.5	59225.8	3538.8
BOT	2289.9	608.8	44139.0	24848.8	660.0	3907.8	9825.9	18844.3
SG	378.3	2216.3	185184.4	71292.4	508.9	25343.6	59647.3	1042.7
DBS	1662.0	1090.6	88097.2	70427.2	6518.2	1053.9	2749.9	45202.1
CS	6844.6	2909.8	53922.0	26773.9	534.0	13087.3	1248.9	4243.8

The weighted values of beneficial and non-beneficial criteria each bank were summarized and are presented in Table 14 using Equations (13-14). This table calculates two scores for each bank: Si^+ for beneficial criteria and Si^- for non-beneficial criteria as the metrics do not represent desirable conditions in an ideal problem.

Table 14. Aggregated weighted scores for beneficial and non-beneficial criteria

Bank	S_{i-}	S_{i+}
SCB	41513.78	724878.7
CITI	57085.02	463584.8
HSBC	10488.36	401163.3
BoA	5119.764	970290
DB	3535.359	342608
Barclays	8204.354	348035.8
BNP	7260.429	415626.6
BOT	2898.609	102225.7
SG	2594.571	343019.2
DBS	2752.537	214048.5
CS	9754.423	99809.98

Table 15 sums up the overall RAM scores and the final ranking for global banks using Equation (15), including for every bank, the relative score (R_{ii}) and rank within the RAM concept. The RAM score as calculated for each bank sums up its performance on beneficial measures and those that are not beneficial. Order the R_{ii} values from highest to lowest and get the final ranking of global banks using the RAM method.

The rank by RAM table gives a cross-sectional view of the world's top banks concerning the financial benchmarks determined by the RAM. In this analysis, the first two positions go to Societe Generale (SG) and DBS rank (DBS), ranking high on the most favorable financial indicators, suggesting good operational health and strategic positioning of the two banking firms as shown in Figure 2. Bank of Tokyo (BOT) and Deutsche Bank (DB) are not far behind the mentioned banks they are the third and fourth competitors, respectively meaning that they have competed as well.

Table 15. Overall, RAM scores and final ranking of global banks.

Bank	R_{ii}	Rank
SCB	1.00033	10
CITI	1.00023	11
HSBC	1.00123	8
BoA	1.0027	5
DB	1.00361	4
Barclays	1.00156	7
BNP	1.00178	6
BOT	1.00398	3
SG	1.00492	1
DBS	1.00447	2
CS	1.00118	9

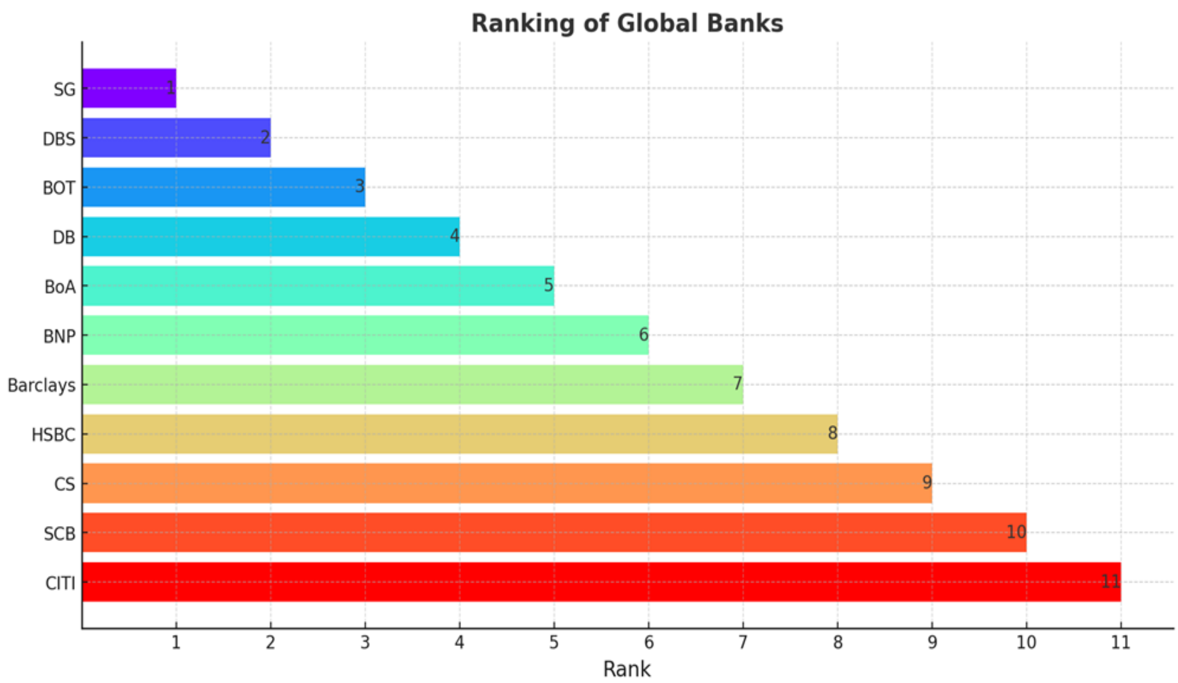

Figure 2. Global ranks for banks.

Standard chartered is in rank four, probably indicating a relatively good but not excellent alignment level, while Bank of America (BoA), BNP Paribas (BNP), and Barclays are in 5th, sixth, and seventh ranks showing more stable but not very high alignment level. HSBC, Credit Suisse (CS), Standard Chartered Bank (SCB) occupy ranks 1 to 6, and CITI Bank (CITI), where the worst rank is for CITI, reflecting that CITI is farther off from the ideal standard performance. These rankings help each bank understand how close they are to the ideal financial standards that will give them a competitive edge and areas that require enhancement. Such RAM-based ranking helps the stakeholders understand the health of the financial banks well enough in order to make the right decision as to which area needs enhancement and which position is competitive enough.

4.5 Comprehensive ranking of global banks using the Borda count method within an integrated MCDM framework

This section brings an overall ranking of the global banks that have applied the Borda count, which integrates the ranks derived from the PIV and RAM. Thus, combining these methods yields the best results on the Borda count, allowing for identifying both highly and moderately stable banks. The results are presented in Table 11 to give the stakeholders a uniformly comparative analysis of the vulnerabilities and the strengths of the selected leading global banks.

Table 11. Aggregate ranking of global banks using the Borda count method based on PIV and RAM rankings.

Bank	Rank by PIV	Borda Score (PIV)	Rank by RAM	Borda Score (RAM)	Aggregate Borda Score	Final Rank
DBS	3	9	2	10	19	1
BoA	2	10	5	7	17	2
SG	8	4	1	11	15	3
CS	1	11	9	3	14	4
BNP	5	7	6	6	13	5
HSBC	7	5	8	4	9	6
SCB	4	8	10	2	10	7
BOT	11	1	3	9	10	8
DB	10	2	4	8	10	9
Barclays	9	3	7	5	8	10
CITI	6	6	11	1	7	11

Table 11 provides the overall ranking of global banks based on the Borda count method, combining the results of the PIV and RAM. Two sets of RAM and PIV ranks were obtained in each bank, and the Borda point score was assigned inversely proportional to the ranks, where higher ranks got more points. The points were then added to arrive at an overall aggregate point. Analyzing the results of the survey in this regard, DBS bank (DBS) has obtained the maximum total Borda score of 19, which is a sound performance of rank 3 based on PIV (score of 9) and rank 2 based on RAM (score of 10). Immediately behind BoA, with an aggregate score of 17, is the next company, while Societe Generale (SG) is ranked third with a score of 15. Such high values indicate that DBS, BoA, and SG align with the benchmark performance level used in both ranking models. Credit Suisse (CS) and BNP Paribas (BNP) have also been evaluated and, as a result, have obtained relatively high scores of 4 and 4, with a total of 14 and 13, respectively. This positioning agrees with their relatively stable ratios in the different metrics assessed in the study. On the other hand, the lowest total score in this research is earned by CITI Bank (CITI), which received only 7 for an overall indicator, indicating the organization's higher divergence from the benchmark in PIV (rank 6) and RAM (rank 11) assessments. Barclays and Deutsche Bank (DB) are also poor performers in the same list and occupy tenth and ninth positions, respectively, showing moderate nearness to the excellent indices. The Borda Count method, therefore, gives a moderate of the PIV and RAM rankings so that both aspects of the strengths of the two banks and the areas of their inefficiency are marked. This result provides an all-around view of each bank's performance and relevancy ranking, which stakeholders can understand with regard to all these factors that define both the stability and operational functionality of the banks. The rankings capture a complex view of how global banks stand relative to one another and reveal promising approaches to achieving more excellent stability among financial systems while pointing to areas where lower-ranked institutions can improve.

5. Discussion

The findings of this research provide a comprehensive assessment of global banks employing an integrated evaluation MCDM technique with SITDE, PIV, and RAM analysis. This allows for a more sophisticated view of every bank's financial solidity and solvency, taking into consideration the one-sided nature of the corresponding financial parameters that cannot be revealed by other approaches. Among the high-ranking banks are DBS, Bank of America, and Societe Generale, which show higher efficiency in liquidity, asset quality, operational efficiency, and profitability indicators. The high conformity with the ideal values indicates a sound financial status and good risk management by their banks (Yalcin et al., 2025). On the other hand, the banks that reported lower aggregate Borda scores, such as CITI and Deutsche Bank, are farther from these reference points and may be considered vulnerable or inefficient in certain specific financial portfolios. In the PIV and RAM rankings, the study presents the relative approach that illustrates various aspects of performance and simultaneously excludes the bias on positive and negative aspects. For instance, DBS falls among those firms with high RAM and PIV, which implies that the firms possess good financial health (Maredza et al., 2022; Roy and Shaw, 2023). While firms such as credit Suisse, which is comparatively proactive in RAM but less effective in PIV, may have an advantage in several factors, they could be more subjectively weak in certain aspects (Wanke et al., 2022).

6. Implications

This study was incredibly significant to stakeholders in the banking and financial industries. These rankings should help the regulators manage resources, emphasizing the banks least compliant with the ideal financial performance indicators of operation, which should point to relatively higher risk. Thus, for investors, the study's multi-criteria evaluation provides a comprehensive view of the financial institutions' bank stability, operation efficiency, and solidity. This serves the investors well because they now make decisions based on the stability and the likelihood of the sustainable performance of each bank in question. The rankings may be helpful for bank management teams to evaluate their own institution's position among its peers, to get ideas about potential advantages, and to identify areas for tactical enhancement. In sum, this paper has provided a valuable means to measure financial wellness and competitive advantage for decision-makers for precision in the unforgiving global financial market.

In evaluating financial performance, integrating SITDE weighting with the PIV and RAM formulations provides a new angle for the MCDM approach. Some of the drawbacks of the methods used in conventional MCDM work include the inability to work with skewed data and the characteristics of financial data. This study eliminates this shortcoming by incorporating SITDE to complement the weighting process and boost its sensitivity. This framework expands MCDM methodologies in finance and provides directions for only future studies of skew-sensitive evaluation models in various and intricate finance scenarios.

7. Conclusion

This paper develops a new technique for aggregating the weight assigned to each criterion through SITDE and ranking global banks by developing and integrating the PIV and RAM techniques into an MCDM model. The results show that there is more reported information about bank performance compared to the traditional financial ratios and that institutions such as DBS, Bank of America, Societe Generale, etc., can be considered the most financially stable and operationally resilient during the crisis. In this way, Skewness in the financial data is handled well at the SITE-weighted level, with account for asymmetry and other peculiarities of the distribution, so that it takes into account all the ranks designated to implement an exact assessment of each bank's results in its functioning in terms of liquidity, profitability, and risk management. This research contributes to the existing literature on MCDM by addressing notable gaps in evaluating bank performance. Traditional MCDM methods often fail to account for the skewed distributions inherent in financial metrics, leading to potential biases in rankings. By incorporating SITDE, this study enhances the robustness and sensitivity of MCDM approaches, providing a valuable methodology that captures the complexity of financial data more effectively. This work paves the way for more refined, data-sensitive evaluation models, setting a foundation for future advancements in financial performance assessment within the banking sector.

Coming to this study�същs limitations, it uses data available to the public, which leaves out some of the factors that can affect the performance of the various banks, especially under the influence of other factors in the external construct. Furthermore, the study's findings cannot be generalized to other periods because the study does not consider factors such as changes in the regulatory environment or generalized macroeconomic conditions that ordinarily may affect the soundness and performances of the institutions under evaluation. Subsequent studies could examine the extension of the described integrated framework to various settings, including regional banks, to determine its effectiveness for various financial contexts. At the same time, including other financial and non-financial standards like environmental or social factors can also give a better picture of the stability and responsibility of the bank. In addition, combining other MCDM methods, such as TOPSIS or VIKOR, with SITDE-weighted PIV and RAM would improve the reliability of bank rankings and offer possibilities for further comparisons. These avenues present a rich potential for future extension of this framework – in essence, advancing instrumentation with greater versatility for application to the banking and finance sectors.

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Authors' Contributions

V. Lava Kumar: Conceptualization, methodology, investigation, writing—original draft preparation. **Shaik Kamruddin**: Conceptualization, methodology. **KS Venkateswara Kumar**: formal analysis, validation. **Sripathi Kalvakolanu**: validation, writing—review and editing. **Jing-Rong Change**: funding acquisition, project administration. **Venkateswarlu Nalluri**: writing—original draft preparation, funding acquisition, project administration. All the authors read and approved the final version of the manuscript.

Does this article screen for similarity?

Yes

Ethics approval

No ethical clearance certificate is applicable for this present study.

Conflict of Interest

The authors have no conflicts of interest to declare. There is also no financial interest to report. The author certifies that the submission is original work and is not under review at any other publication.

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V. Lava Kumar, Shaik Kamruddin, K.S. Venkateswara Kumar, Sripathi Kalvakolanu, Venkateswarlu Nalluri, Jing-Rong Chang, A Multi-Criteria Decision-Making Approach to Improve Criteria Ranking and Weighting: Integrating SITDE Weighting With PIV and RAM Techniques, Asian Journal of Interdisciplinary Research, 8(2), (2025) 1-20. https://doi.org/10.54392/ajir2521