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A Modified EATWIOS Framework for Efficiency Assessment: A Case Study on the Banking Sector

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ABSTRACT

Efficiency assessment of banks is a complex decision that depends on various factors. This paper proposes the creation of a framework for efficiency assessment for firms by considering capital structure, asset quality, and financing costs. This present paper proposes a comprehensive framework for efficiency assessment by modifying the EATWIOS method. This present paper incorporates slack efficiency, peer evaluation, and reference-based normalization into the conventional EATWIOS method. This paper proposes the use of the MPSI (modified preference selection index) method for determining the weights of the criteria. This paper proposes conducting a multi-period assessment from FY 2020–21 to FY 2024–25 for 12 public sector banks and 14 private sector banks. The results show significant variations in efficiency among banks. The proposed framework has shown improved discriminative ability and ranking efficacy for various settings of the model. The robustness is verified using sensitivity analysis, rank correlation assessment, and variation analysis. The results will be helpful for bank managers in developing policies for maintaining financial stability and risk management to improve efficiency.

1. Introduction

The banking sector is the basis for financial intermediation in emerging countries. The commercial banks are operating in an increasingly regulated environment, which is determined by capital adequacy ratios, asset quality assessment methods, recapitalization programs, and structural consolidation through mergers. These developments in the institutional framework have contributed greatly to changes in the efficiency of bank operations. Efficiency cannot be considered only as cost-cutting or revenue-generating measures; rather, it represents the optimization of intermediation processes, capital structure, and asset quality.

Capital structure and asset quality are considered external variables that affect efficiency but are not necessarily part of the production technology itself. Empirical evidence shows that capital

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structure has a significant effect on risk-taking activities and frontier efficiency [1-3]. Capital requirements affect funding costs and the weighted average cost of capital (WACC) [4-5], while optimal bank capitalization involves trade-offs between stability and cost competitiveness [6]. Asset quality has a significant effect on efficiency and stability [7-9]. These results suggest that capital structure and asset quality are not only variables but also basic components of banking output.

Some researchers have noted that differences in efficiency across ownership types [10], scale economies generated by mergers [11], and enhanced regulatory restrictions have introduced structural heterogeneity. Asset quality concerns, especially the high level of NPAs, have shaped lending behavior and provisioning decisions. In this context, a study on efficiency that ignores capital costs and asset quality could result in inconclusive or dubious results.

Data Envelopment Analysis (DEA) has been widely used in banking efficiency evaluation due to its ability to handle multiple inputs and outputs without requiring any parametric specifications. Recent studies have used DEA to measure the efficiency of commercial banks in emerging areas [12-14]. In the emerging market, such as India, the use of the meta-frontier and two-stage DEA models has been made to examine the effects of ownership heterogeneity and efficiency change due to mergers and acquisitions [15,16]. Furthermore, the use of the Malmquist and SFA extensions has been made to examine the changes in productivity during consolidation periods. Although the use of slack-based and undesired output models has been made to include credit risk in the form of NPAs [14,17], the ability to examine structural stability in the frontier function is still lacking.

Efficiency Analysis Technique with Input and Output Satisficing (EATWIOS) has emerged as a prominent technique in the field of DEA, which can replace the conventional DEA framework in evaluating efficiency. DEA is one of the most popular techniques used to measure efficiency in organizations, which is a non-parametric method to measure the efficiency of Decision-Making Units (DMUs) relative to the frontier. Although DEA provides a sound foundation in theory, the process of solving optimization problems for each DMU is complex. Furthermore, the conventional DEA model, which is used to measure efficiency, only considers proportional efficiency and may not capture other types of inefficiency unless slack-based models are applied. DEA may not have discrimination power if the number of inputs and outputs is large compared to the number of DMUs.

Unlike DEA, EATWIOS employs distance-based calculations utilizing optimal input and output values, which makes it easier to calculate and less computationally intensive to implement [18-19]. This characteristic further helps in reducing the complexity of calculations involved in determining efficiency. Additionally, EATWIOS allows researchers to incorporate satisficing levels and multi-criteria weighting systems, thus making it easier to implement a more flexible approach to modeling decision-makers' preferences than the conventional DEA approach [20-21]. Another advantage is that EATWIOS allows for the seamless integration of various MCDM approaches, such as entropy, SWARA, and fuzzy approaches, to name a few, to improve the depth and strength of analysis [22-23]. Real-world applications of EATWIOS in areas such as supply chain management, logistics, and financial performance analysis have shown that EATWIOS provides improved interpretability and discriminatory power while maintaining methodological simplicity [24-26]. Therefore, EATWIOS can be considered a flexible and practical approach to efficiency analysis that improves and, in some cases, exceeds the DEA-based approach.

However, the conventional EATWIOS approach has several methodological flaws that require the development of a better version. First, the conventional EATWIOS approach is only capable of calculating radial efficiency using aggregated input and output values to obtain a single ratio of efficiency. This approach inherently assumes equal improvement in all input and output values, thus not taking into account non-radial inefficiencies or goal value deviations. This implies that DMUs approaching the optimal frontier in aggregate terms may still be highly inefficient in terms of other values not considered by the conventional approach.

Secondly, the conventional EATWIOS method compares DMUs only with ideal standards, without considering peer comparisons among similar units. Accordingly, the proposed method may overlook the context of the decision set and the relative position of individual DMUs. Third, the conventional EATWIOS method calculates efficiency scores only from distance ratios, which may limit the discrimination of similar Decision-Making Units (DMUs) with comparable distance measures.

The Modified EATWIOS model overcomes the above limitations by incorporating two major modifications: (i) average slack efficiency, which measures non-proportional inefficiency on all dimensions, and (ii) distance-based peer comparison, which incorporates similarity-based peer comparisons among DMUs. The modified approach provides a more comprehensive and nuanced analysis of operational efficiency by incorporating radial efficiency, slack inefficiency, and peer comparisons into a unified framework. Table 1 presents a basic comparison of the modified EATWIOS approach with the DEA and the conventional EATWIOS method.

Thus, the current study aims to find an answer to the subsequent research questions:

Q1. To what extent do banks differ in their efficiency based on capital structure and asset quality?

Q2. How do private banks differ from public sector counterparts?

Q3. How can a composite stability measure be developed that offers a comprehensive evaluation of efficiency and reliability?

The subsequent sections of the paper are organized as follows. Section 2 examines the literature concerning banking efficiency and applications of the methodological frameworks. Section 3 delineates the case study. Section 4 outlines the proposed methodology. Section 5 reports the findings and discusses the insights obtained from the outcomes. Section 6 exhibits the results of the robustness analysis. Section 7 highlights the research implications. Ultimately, Section 8 ends the paper with concluding remarks.

Table 1
Comparison of the modified EATWIOS method with DEA and the traditional EATWIOS

Feature of the method	DEA	Classical EATWIOS	Modified EATWIOS
Efficiency calculation	Frontier-based (radial efficiency)	Distance-based	Hybrid
Optimization	Yes (Solve linear programming model)	No	No
Slack inefficiency consideration	Yes (Slack-based DEA models)	No	Yes (Average slack inefficiency)
Peer benchmarking	Frontier projection	No	Internal efficiency (Distance-based; relative to ideal input and output values) and peer evaluation
Computational complexity	High	Low	Moderate
Discrimination power of the model	Moderate (many DMUs may have the same efficiencies)	Moderate (Scores are continuous and distinct)	High (multiple performance dimensions)

2. Literature Review

2.1 Measuring banking efficiency

A large number of research studies have been conducted on banking efficiency from different angles. DEA is widely used to compare the efficiency of financial institutions. Various studies have been conducted using DEA to analyze the performance of the banking sector in different regions, such as the technical efficiency of commercial banks in Africa [12] and the operating efficiency of insurance companies in Vietnam [13]. In addition, advanced DEA models, such as slack-based DEA and two-stage DEA models, have been used to analyze banking efficiency in emerging markets [14-15].

However, recent studies have utilized DEA in conjunction with other analytical techniques to improve the explanatory power of efficiency analysis. Shi *et al.* [27] combined DEA with machine learning techniques like random forests and Shapley value explanations to analyze financial viability in the banking sector. Fukuyama *et al.* [28] also proposed combining causal modeling with DEA to enhance the explanatory power of performance analysis results. Such developments indicate that there is a growing need for efficiency analysis.

Apart from technical advancements, various studies have also been conducted on the determinants and implications of banking efficiency. For example, Benbachir [29] has used the two-stage DEA-Tobit approach to investigate the determinants of efficiency in the MENA banking sector, while Katuka *et al.* [30] have examined the relationship between cost efficiency and non-performing loans in developing countries. Other studies have also emphasized the importance of capital structure, asset quality, and operational efficiency on bank efficiency [31, 32]. Recently, various meta-analytical reviews have also emphasized the increasing methodological variances of efficiency measurement, along with the possibility of using new frameworks of efficiency measurement, other than frontier ones [33].

Several studies have explored banking and financial performance in terms of various analytical tools other than the traditional efficiency measuring tools. For instance, Hasan *et al.* [34] used stochastic frontier analysis to measure the efficiency of Islamic commercial banks in Indonesia. Chen *et al.* [35] explored the correlations between operational efficiency, market efficiency, and sustainable development in the banking industry. Most of the literature has focused on the effect of financial structure and risk factors on banking performance. For instance, Ben Abdallah and Bahloul [36] explored the effect of solvency and liquidity ratios on bank profitability, while Urbonaviciute [37] explored the effect of capital rules on the dynamics of non-performing loans in European banks. Other literature has highlighted the importance of capital structure and operational efficiency in determining business performance [3, 38-40].

From the literature, it can be understood that financial performance evaluation is a complex process that requires various analytical tools to ensure a comprehensive evaluation. Amirteimoori and Allahviranloo [39] proposed a new DEA-based model to improve efficiency differentiation in proficient banks. For instance, Atiningsih [41] explored the effect of audit quality and capital structure on corporate performance in terms of earnings management. Similarly, Lim *et al.* [42] explored the effect of employee tenure on the weighted average cost of capital, while Syafaat and Timuriana [43] explored the performance of Islamic banks in terms of essential financial parameters.

Numerous recent studies have utilized MCDM frameworks to assess banking efficiency and financial performance. Işık *et al.* [44] introduced a spherical fuzzy expert-based MCDM model to assess efficiency, productivity, and sustainability performance in Islamic banks, illustrating the efficacy of fuzzy information in managing uncertainty in financial decision-making. Likewise, Işık *et al.* [45] developed a hybrid MCDM framework to evaluate the performance of Pakistani commercial banks, underscoring the growing use of integrated decision-support models in banking analysis. Aydın [46] proposed a hybrid MCDM model for evaluating banking performance, highlighting the advantages of integrating several decision-making processes. Additional research has utilized fuzzy extensions of traditional ranking methodologies. Jana *et al.* [47] employed a fuzzy TOPSIS methodology to assess the financial efficiency of private banks, whereas Peci *et al.* [48] combined fuzzy AHP and TOPSIS to evaluate performance in the Albanian banking industry. Wanke *et al.* [49] recently presented a quantum-inspired MCDM methodology to analyze the correlation between AI-driven financial markets and bank performance in China, demonstrating the growing methodological complexity in financial efficiency research.

2.2 Applications of the EATWIOS method

The popularity of the EATWIOS method in various decision-making situations has increased due to its ability to measure efficiency without being bound to complex optimization models. The core advancement of the method, spearheaded by Michael L. Peters, Stefan Zelewski, and colleagues, has demonstrated the importance of satisficing levels in measuring the efficiency of input quantities [19]. Since then, several other advancements have been made to include various constraints, thus proving the applicability and flexibility of the method in various decision situations [18].

Recently, several applications of the EATWIOS method have been seen in various industries. Aytekin *et al.* [20] have applied DEA and EATWIOS to measure the innovation efficiency of European countries, thus proving the applicability of the method in various decision situations. Çilek and Karavardar [22] have applied entropy weighting and EATWIOS to measure the efficiency of public banks in Turkey. Similarly, the applicability of the method has been demonstrated in supply chain and logistics. Görçün *et al.* [23] have applied fuzzy SWARA and EATWIOS to measure the global supply chain efficiency of various retails in the world. Similarly, Görçün [24] has applied the MCDM and EATWIOS model to measure the efficiency of container ports in the Black Sea region.

Recently, several advancements have been made to the EATWIOS method to enhance its applicability in various decision situations. Gamal *et al.* [21] have applied the EATWIOS method to measure the efficiency of logistics and autonomous systems. Similarly, Kaya *et al.* [25] have applied the EATWIOS method to measure the efficiency in the maritime transport industry and to identify the relationship between operational and financial efficiency. Although several advancements have been made to the EATWIOS method, most of the recent literature has demonstrated the applicability of the method in various decision situations through hybrid models. There has been relatively less emphasis on advancing the efficiency model itself.

2.3 Applications of the MPSI method

Recent research has been focusing on exploring new hybrid MCDM models that incorporate the Modified Preference Selection Index (MPSI) to enhance the robustness of decision performance evaluations. The major motivation behind the incorporation of the MPSI technique into MCDM models lies in its potential to produce objective criterion weights using data dispersion, hence reducing the level of subjectivity involved in decision choices. For instance, Akbulut and Aydın [50] proposed a new hybrid MSD-MPSI-RAWEC model to evaluate the performance of Turkish banks using the MCDM technique. The study demonstrated the effectiveness of using the hybrid model to produce more accurate financial performance evaluations. Ersoy and Özçalıcı [51] proposed a new hybrid MCDM model to compare the performance of European Union countries with respect to the achievement of Sustainable Development Goals (SDGs). The study demonstrated the effectiveness of the MPSI technique as a decision support tool for conducting comparative evaluations.

Researchers have also been incorporating the MPSI technique with other sophisticated ranking techniques to enhance the robustness of MCDM models. For instance, Gligorić *et al.* [52] proposed a new hybrid model combining the MPSI technique with the MARA technique to support decision choices on selecting underground mine support systems. The study demonstrated the effectiveness of using the hybrid model to produce more accurate decision choices. Wittig Vianna *et al.* [53]

applied the MPSI-CoCoSo model to compare the performance of OECD countries with respect to the achievement of energy transition. The study demonstrated the effectiveness of using the hybrid model to produce more accurate sustainability evaluations. Güçlü [54] conducted comparative evaluations using the MPSI technique integrated with other techniques such as DNMARCOS, AROMAN, and MACONT to produce more accurate ranking results. Other studies have focused on benchmarking and the way we measure performance, including topics such as the evaluation of supply chain performance [55] and the financial performance benchmarking of IPO companies via a hybrid MPSI-RBNAR method [56].

Researchers have been using these sophisticated MCDM models to support decision choices in various fields other than finance and banking. For instance, Çelebi Demirarslan *et al.* [57] applied the MPSI technique to compare the quality of life of countries in the Asian region. Zhang *et al.* [58] proposed an AI-based optimization model to support decision choices on multi-axial vibration fatigue using the MCDM technique.

2.4 Research gaps and contributions of the current study

This is due to the fact that the body of literature on banking efficiency is continually expanding. Consequently, there is a critical need for a comprehensive framework for evaluating the overall effectiveness of financial services. Past literature has mainly relied on frontier methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) in assessing how efficiently banks in various countries operate. Though this literature has significantly contributed to our understanding of bank efficiency, there are still some conceptual and methodological limitations that warrant further investigation.

For instance, most past literature has viewed capital structure, capital costs, and asset quality as exogenous factors that influence bank efficiency. However, a significant number of literature works have examined how capital structure, capital costs, and asset quality influence bank profitability. However, they rarely incorporate these factors in evaluating bank efficiency. Hence, this literature might not effectively link bank stability indicators with bank efficiency.

In addition, even though DEA and its variants are largely preferred in evaluating bank efficiency due to their popularity, they have some critical limitations. First, in using conventional DEA in evaluating bank efficiency, banks have to solve a linear program for each decision-making unit. This makes DEA computationally expensive and less discriminatory in situations where there is a significant number of DMUs on the frontier. Though advanced DEA variants such as Slack-based DEA and meta-frontier analysis aim to address some of DEA limitations, they are still largely based on mathematical optimization.

The Efficiency Analysis Technique with Input and Output Satisficing (EATWIOS) has recently become a viable alternative because of its distance-based approach and strong conceptual foundation. EATWIOS and its hybrid variants have been successfully used in innovation policy, supply chain management, and banking performance analysis. However, most of the recent research has been focused on combining EATWIOS with weighting approaches (such as entropy or SWARA) or fuzzy decision models, rather than attempting to enhance the underlying structure of the efficiency analysis process itself. The traditional EATWIOS model does not address slack inefficiency or peer comparison, which may affect its ability to distinguish units that are at similar distance levels.

On the other hand, the Modified Preference Selection Index (MPSI) approach has recently gained popularity in hybrid multi-criteria decision support, but its application has been largely confined to weighting or ranking criteria. There is a significant research gap in using MPSI in efficiency-related systems, particularly in banking performance analysis. This represents an opportunity to integrate objective weighting approaches with advanced efficiency analysis techniques to enhance the methodological rigor.

This paper breaks new ground by incorporating several significant aspects that were not considered in previous works.

i. It proposes an extension of the EATWIOS model by integrating average slack efficiency and peer review in distance-based assessment. This allows for a better evaluation of both radial and non-radial efficiency in a bank's operations.
ii. It combines the MPSI objective criterion weighing with the extended version of the EATWIOS model. The study revealed a clear trend in using a combination of MPSI with other MCDM techniques to stabilize rankings, eliminate biases, and increase robustness in evaluation. Most studies have concentrated on integrating weighing and ranking, while few have attempted to incorporate MPSI in efficiency-based models and develop new extensions in MCDM techniques.
iii. The study establishes a clear and direct relationship between capital structure, financing costs, and asset quality measures such as NPAs in efficiency evaluation. This establishes a clear and direct relationship with operational efficiency and financial stability in banking systems.
iv. The study presents an empirical model of efficiency evaluation in Indian banks, providing a clear and detailed comparison of public and private sector banks over a period of time and providing clear insights into differences in fundamental efficiency and financial stability in a developing economy.
v. The study proposes a new and unique efficiency evaluation model that combines different aspects of efficiency evaluation in a single framework while improving discrimination efficiency without increasing complexity in evaluation techniques.

3. Case study

This section describes the input and output variables, the data collection process, and the conceptual steps of the proposed R-DEA methodology.

3.1 Selection of input and output variables

The input and output variables are selected from related contributions to the literature on banking efficiency measurement. Table 2 outlines a short description of the input and output variables.

Table 2
Description of the input and output variables

S/L	Variable	UOM	Type (in DEA)	Goal (MCDM)	Remarks
C1	Deposit	Rs. Crore	Input	Max	An increase in deposits lowers funding costs, enhances lending capacity, improves solvency, and indicates customers' trust and growth prospects.
C2	Operating Expense	Rs. Crore	Input	Min	Lower operating costs result in better operational efficiency.
C3	Equity	Rs. Crore	Input	Max	A higher equity value indicates the capital adequacy to withstand losses, safeguard depositors' funds, and meet regulatory requirements.
C4	Total Loans & Advances	Rs. Crore	Input	Max	Generally, a higher lending activity reflects better intermediation and income generation.

Table 2
Continued

S/L	Variable	UOM	Type (in DEA)	Goal (MCDM)	Remarks
C5	Total Assets	Rs. Crore	Input	Max	Greater asset utilization indicates stronger bank capacity and economies of scale. It is an indicator of stability.
C6	WACC	Value	Output	Min	A lower value indicates lower financing costs, improved financial health, greater efficiency, and higher value generation.
C7	NPA	Value	Output	Min	A lower value indicates superior asset quality, higher profitability, and lower risk.

3.2 Data collection

The present work compares 26 DMUs (12 public-sector and 14 private-sector banks in India) as a case study (Table 3). The data were collected from the Moneycontrol database. Tables A1 to A5 (in Appendix A) provide the values of the input and output variables over five consecutive financial years, Fy 2020-21 to Fy 2024-25. We perform the efficiency assessment for each year separately. The number of DMUs (=26) is greater than 3 X (number of input and output variables = 7). Hence, it indicates data sufficiency.

Table 3
Description of the DMUs

DMU	Name of the Banks	DMU	Name of the Banks
DMU1	Bank of Baroda	DMU14	City Union Bank Ltd.
DMU2	Bank of India	DMU15	D C B Bank Ltd.
DMU3	Bank of Maharashtra	DMU16	Dhanlaxmi Bank Ltd.
DMU4	Canara Bank	DMU17	Federal Bank Ltd.
DMU5	Central Bank of India Ltd.	DMU18	H D F C Bank Ltd.
DMU6	Indian Bank	DMU19	I C I C I Bank Ltd.
DMU7	Indian Overseas Bank	DMU20	Indusind Bank Ltd.
DMU8	Punjab & Sind Bank	DMU21	Jammu & Kashmir Bank Ltd.
DMU9	Punjab National Bank	DMU22	Karnataka Bank Ltd.
DMU10	State Bank of India	DMU23	Karur Vysya Bank Ltd.
DMU11	Uco Bank	DMU24	Kotak Mahindra Bank Ltd.
DMU12	Union Bank of India	DMU25	South Indian Bank Ltd.
DMU13	Axis Bank Ltd.	DMU26	Yes Bank Ltd.

4. Proposed methodology

This section outlines the steps of the proposed methodological framework. As stated earlier, the current study employs the MPSI method for criteria weighting and the modified EATWIOS model to derive the efficiencies of the DMUs and rank them.

4.1 MPSI method for criteria weighting

The procedural steps of the MPSI method in the current study are described below. We follow the steps mentioned in [52, 55], except for the normalization scheme. The current study uses a reference-based normalization approach [59].

Step 1. Formation of the initial decision matrix

Suppose,

Let, $A_i (i = 1,2,\dots,m)$ are the DMUs compared based on $n$criteria. Let, a_{ij}indicates the performance of the i^{th}DMU subject to j^{th}criterion. Thus, the decision matrix includes both input and output criteria that represent the operational characteristics of each DMU. The decision matrix is given below.

$$X = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

Step 2. Normalization of the initial decision matrix

The reference-based normalization is done as follows.

$$a_{ij}^{*} = 1 - \frac{|a_{ij} - r_j|}{\underset{i}{Max}(a_{ij}) - \underset{i}{Min}(a_{ij})}; i = 1,2,..,m; j = 1,2,..,n \tag{2}$$

The present work obtains the reference as follows.

$$r_j = \begin{cases} \underset{i=1,2,..,m}{Max}(a_{ij}); j \in B \\ \underset{i=1,2,..,m}{Min}(a_{ij}); j \in NB \end{cases} \tag{3}$$

Normalization is done to remove dimensional inconsistencies and achieve uniform measurement scaling. The reference-based normalization assesses proximity to the goal, enhancing interpretability and the significance of decision-making [59].

Step 3. Obtain the performance variation (PV) values for the criteria

The PV values indicate the variability of the performance of the alternatives under the effects of the corresponding criteria. PV value is calculated as the total squared deviation from the mean performance under a specific criterion.

The PV value for j^{th}criterion is obtained as

$$P_j = \sum_{i=1}^{m} (a_{ij}^{*} - \overline{a_j^{*}})^2 ; j = 1,2,\dots n \tag{4}$$

$$\overline{a_j^{*}} = \frac{\sum_{i=1}^{m} a_{ij}^{*}}{m} \tag{5}$$

Step 4. Determine the criteria weights

The weight for j^{th}criterion is derived in terms of its proportional contribution to the overall total square deviation across all the criteria. A criterion having the higher PV value is treated as a significant influencer for the performance of the alternatives or DMUs. Accordingly, the weights are calculated as follows.

$$W_j = \frac{P_j}{\sum_{j=1}^{n} P_j}; W_j \geq 0; \sum W_j = 1 \tag{6}$$

4.2 Modified EATWIOS method

Suppose there are $j = 1,2,..,k$input variables and $j = 1,2,...,g$output variables. Hence, $n = k + g$.

Step 1. Formulate the decision matrix as earlier (1).

Step 2. Normalize the decision matrix as stated earlier (2)-(3).

Step 3. Construct the Weighted Normalized Matrix.

The elements of the weighted normalized decision matrix are derived as follows.

$$\vartheta_{ij} = a_{ij}^{*} \times w_j \tag{7}$$

This step highlights the impact of the criteria reflected in the calculated weighted values.

Step 4. Determination of the performance efficiency (PE) scores of the DMUs

Step 4(a). Identify the ideal input and output values

This step is required to assess the deviations from optimal performance. The ideal values are the best observed normalized performance values under the corresponding criteria. The ideal values are obtained as follows.

$$\vartheta_j^* = \begin{cases} \underset{i}{Max}\left(\vartheta_{ij}\right); j = 1,2,..,g(output) \\ \underset{i}{Min}\left(\vartheta_{ij}\right); j = 1,2,..,k(input) \end{cases} \tag{8}$$

The concept of efficiency is getting more outputs with fewer inputs.

Step 4(b). Calculation of Output and Input Distances

The separation of each DMU from ideal values is calculated using the Minkowski distance measures [60]. This is an improvement made in the modified EATWIOS method. The Minkowski distance measure provides greater discriminatory power and robustness to extreme observations (outliers) [60]. Accordingly, the distances of each DMU from the optimal input and output levels are obtained as follows.

$$\text{Output distance: } d_{ij}^{op} = \left(\frac{\left|\vartheta_j^* - \vartheta_{ij}\right|}{m}\right)^{\frac{1}{m}}; j = 1,2,..,g \tag{9}$$

$$\text{Input distance: } d_{ij}^{ip} = \left(\frac{\left|\vartheta_{ij} - \vartheta_j^*\right|}{m}\right)^{\frac{1}{m}}; j = 1,2,..,k \tag{10}$$

Step 4(c). Calculation of the PE values of the DMUs

We follow the conventional EATWIOS approach to calculate the PE values of the DMUs as follows.

$$\xi_i = \frac{\sum_{j=1}^{g} d_{ij}^{op}}{\sum_{j=1}^{k} d_{ij}^{ip}} \tag{11}$$

The PE value reflects the ability of a DMU to generate the output (close to the output ideal value) with respect to the given input value (measured in terms of distance to the input ideal value). Based on the calculated PE scores, the efficiency frontier is formulated.

Step 5. Determination of the slack-based efficiency (SE) scores

This is a novel extension of the classical EATWIOS method. The conventional EATWIOS method does not calculate SE scores. The classical EATWIOS method considers only radial efficiency measures, such as the PE score. However, SE scores capture non-proportional inefficiencies that radial efficiency measures often fail to indicate. The calculation of the SE scores highlights hidden performance gaps given specific inputs or outputs. The incorporation of the SE scores helps to better discriminate the DMUs. As a result, it enhances the accuracy and reliability of performance efficiency assessment.

The concept of the slack-based measures (SBM) is popular in DEA models. However, in our modified EATWIOS method, we do not follow the SBM concept. Instead, we use a deviation-based approach that directly operates on the initial decision matrix. This approach offers many advantages over the SBM. First, it is computationally simple to execute. Secondly, SBM is sensitive to outliers. Third, the deviation-based measure pinpoints the criterion-specific inefficiencies.

Step 5(a). Identify the target values for the criteria (as evident from the initial decision matrix)

The target value is the best observed value (most desirable performance level) for a specific criterion. Eventually, the target values are obtained using (3). Assessing these target values helps benchmark the performance of the DMUs in a realistic manner.

Step 5(b). Calculate relative slack values

The slack value indicates the deviation from the corresponding target value. The slack value of the i^{th}DMU under the j^{th}criterion is obtained as follows.

$$\theta_{ij} = |a_{ij} - r_j| \tag{12}$$

Therefore, the relative slack value (RSV) is given by the following.

$$\Delta_{ij} = \frac{\theta_{ij}}{\underset{i}{Max}(a_{ij}) - \underset{i}{Min}(a_{ij})} \tag{13}$$

RSVs provide scale-independent measurement of inefficiencies.

Step 5(c). Obtain the average slack value (ASV)

The ASVs are obtained by using Eq. 14 as follows.

$$\overline{\Delta_i} = \frac{1}{k+g}\left(\sum_{j=1}^{k} \Delta_{ij} + \sum_{j=1}^{g} \Delta_{ij}\right) \tag{14}$$

ASVs provide the non-radial inefficiencies to capture the non-proportional effects.

Step 5(d). Obtain the SE values

The SE values are calculated as follows.

$$\zeta_i = \frac{1}{1+\overline{\Delta_i}} \tag{15}$$

Step 6. Compute the internal efficiency (IE) values

The IE values are the combined result of radial (PE) and non-radial (SE) efficiencies. It is obtained as follows.

$$\psi_i = \beta\xi_i + (1-\beta)\zeta_i; 0 \leq \beta \leq 1 \tag{16}$$

The parameter βindicates the proportionate emphasis on PE and SE. Hence, IE is a balanced measure of two types of efficiencies for each DMU.

Step 7. Conduct the peer evaluation

This is another significant improvement to the classical EATWIOS method. By integrating the peer benchmarking, the modified EATWIOS offers a comprehensive, all-round assessment of the DMUs. The steps are delineated below.

Step 7(a). Obtain the separations between DMUs

The separation between any two DMUs is obtained as follows.

$$\partial_{pq} = \sum_{j=1}^{k} |a_{pj} - a_{qj}| + \sum_{j=1}^{g} |a_{pj} - a_{qj}| \tag{17}$$

Step 7(b). Convert the separation into similarity value

Proximity is transformed into a similarity value as follows.

$$\varphi_{pq} = \frac{1}{1+\partial_{pq}} \tag{18}$$

Step 7(c). Obtain the peer weights

The peer weights are obtained as follows.

$$\boldsymbol{\omega_{pq}} = \frac{\boldsymbol{\varphi_{pq}}}{\sum_{p=1}^{m} \boldsymbol{\varphi_{pq}}} \tag{19}$$

Step 7(d). Calculate the cross-efficiency (CE) values for the peer evaluation

The CE values for the DMUs are obtained as follows.

$$\mu_i = \sum_{p=1}^{m} \omega_{pi}\xi_p \tag{20}$$

Step 8. Derive the final overall efficiency (OE) values of the DMUs

The OE values are calculated by linearly combining the IE and CE values, as per Eq. (21).

$$S_i = \alpha\psi_i + (1-\alpha)\mu_i \tag{21}$$

The ranking of the DMUs is made based on the OE values. The DMU with the highest OE value is ranked first.

4.3 Borda count method

The Borda count method is used to amalgamate various rankings. In this paper, we apply the modified EATWIOS method to rank the DMUs for five consecutive financial years. We apply the steps of the Borda count method [61].

Figure 1 displays the procedural steps of the research methodology.

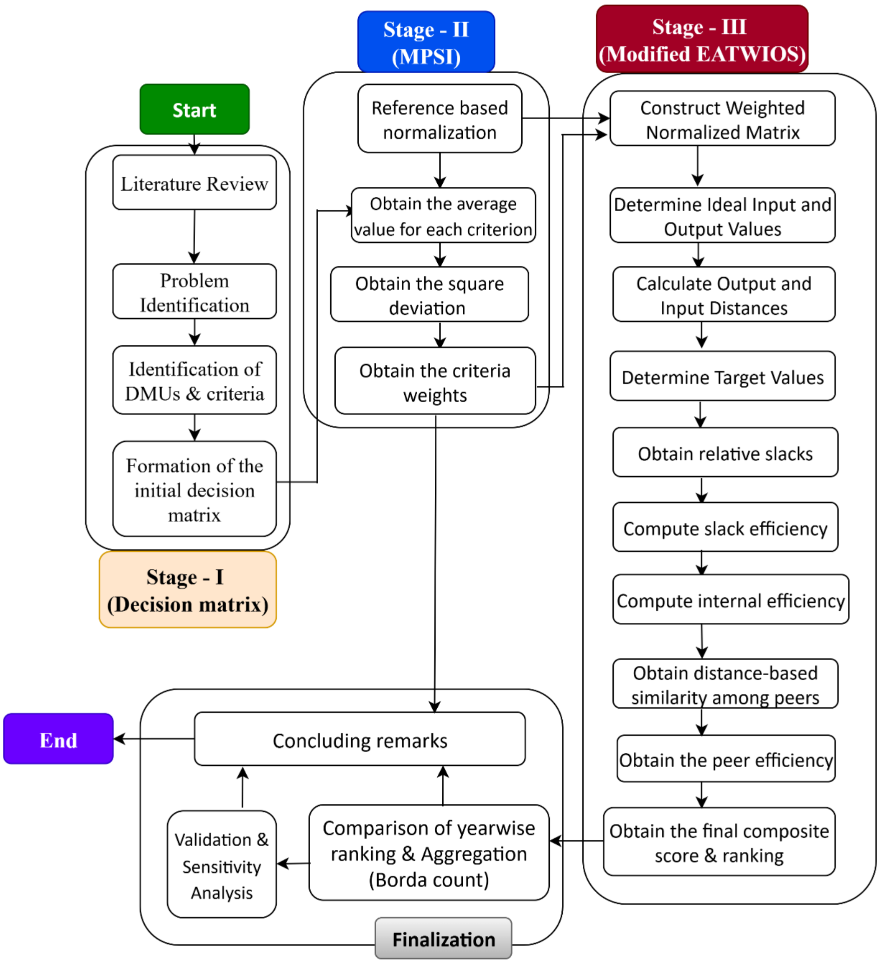

Fig. 1. Flowchart of the procedural steps of the research methodology

5. Findings

This section reports key findings of the data analysis using our proposed framework: MPSI and modified EATWIOS methods. The initial decision matrices for all years are provided in Appendix A (Tables A1-A5). First, we normalize the decision matrix using the reference-based normalization approach (Eq. 2-3). For example, for FY 2024-25, the reference values are given as (5382189.53, 1900.71, 19256.59, 4194694.21, 6691035.91, 0.0482, 0.0018). It may be noted that the criteria C2, C6, and C7 are of a non-beneficial type. The normalized decision matrix (FY 2024-25) is given in Table 4. The normalized decision matrices for all other years are exhibited in Tables A6-A9.

Table 4
Normalized decision matrix (FY 2024-25)

Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.2713	0.7481	0.0501	0.2888	0.2642	0.7528	0.6460
DMU2	0.1492	0.8520	0.2335	0.1534	0.1538	0.7024	0.4336
DMU3	0.0543	0.9572	0.3971	0.0540	0.0526	1.0000	1.0000
DMU4	0.2685	0.7413	0.0907	0.2518	0.2495	0.6299	0.5398
DMU5	0.0739	0.9235	0.4680	0.0655	0.0693	0.8627	0.9912
DMU6	0.1344	0.8761	0.0664	0.1337	0.1284	0.7409	0.8319
DMU7	0.0551	0.9426	1.0000	0.0564	0.0565	0.7499	0.6726
DMU8	0.0212	0.9769	0.3660	0.0205	0.0216	0.5756	0.3097
DMU9	0.2890	0.7319	0.1160	0.2570	0.2701	0.7593	0.8053
DMU10	1.0000	0.0000	0.0427	1.0000	1.0000	0.7630	0.7434
DMU11	0.0517	0.9440	0.6498	0.0486	0.0516	0.8080	0.7168
DMU12	0.2411	0.7738	0.3941	0.2259	0.2225	0.6498	0.6018
DMU13	0.2156	0.7362	0.0284	0.2497	0.2388	0.5297	0.8496
DMU14	0.0089	0.9897	0.0000	0.0099	0.0089	0.4608	0.0531
DMU15	0.0082	0.9887	0.0125	0.0093	0.0088	0.3564	0.1681
DMU16	0.0000	1.0000	0.0167	0.0000	0.0000	0.6873	0.2832
DMU17	0.0499	0.9450	0.0217	0.0537	0.0496	0.4595	0.7699
DMU18	0.5029	0.4155	0.0360	0.6306	0.5844	0.5033	0.7788
DMU19	0.2971	0.6913	0.0704	0.3236	0.3156	0.5395	0.7876
DMU20	0.0736	0.8846	0.0367	0.0802	0.0805	0.0000	0.3186
DMU21	0.0247	0.9759	0.0019	0.0221	0.0227	0.7799	0.4602
DMU22	0.0165	0.9824	0.0158	0.0157	0.0155	0.5177	0.0000
DMU23	0.0160	0.9369	0.0045	0.0172	0.0152	0.4672	0.9823
DMU24	0.0900	0.8888	0.0480	0.0992	0.1014	0.6606	0.8850
DMU25	0.0171	0.9808	0.0098	0.0177	0.0160	0.6028	0.3451
DMU26	0.0500	0.9257	0.3230	0.0564	0.0608	0.5839	0.8938

Then we proceed to apply the steps of the MPSI method (Eq. 4-6) to determine the criteria weights. Table 5 reports the calculated PV values and criteria weights for all years. We use these calculated criteria weights to determine the IE, CE, and OE values for the DMUs and subsequently rank them.

Next, we execute the steps of the modified EATWIOS method to determine the IE, CE, and OE values of the DMUs. It may be noted that in our case, C6 and C7 are the output criteria. First, we construct the weighted normalized decision matrix using Eq. 7. Then, we identify the ideal values for input and output criteria (Eq. 8). Next, we derive the distances of the DMUs to the ideal values for both input and output criteria (Eq. 9-10). The separations of the DMUs from the ideal values (input and output criteria) for all years are reported in Tables A10-A14. Next, we use Eq. 11 to obtain the PE scores of the DMUs (Table 6).

Table 5
Year-wise calculated criteria weights (MPSI method)

Year	Criteria	C1	C2	C3	C4	C5	C6	C7

Fy 20-21	PV	1.0535	1.0396	1.3573	1.1244	1.0539	1.0049	2.1159
	Weight	0.1204	0.1188	0.1551	0.1285	0.1205	0.1149	0.2418
Fy 21-22	PV	1.0592	1.0271	1.4414	1.1506	1.069	1.3365	1.8724
	Weight	0.1183	0.1147	0.1609	0.1285	0.1194	0.1492	0.2091
Fy 22-23	PV	1.0857	1.076	1.4502	1.1525	1.0888	1.2265	1.8735
	Weight	0.1213	0.1202	0.162	0.1287	0.1216	0.137	0.2093
Fy 23-24	PV	1.1201	1.1464	1.471	1.2916	1.1875	0.9029	1.8054
	Weight	0.1255	0.1284	0.1648	0.1447	0.1331	0.1012	0.2023
Fy 24-25	PV	1.1407	1.1759	1.5107	1.2476	1.1975	0.9378	2.145
	Weight	0.1219	0.1257	0.1615	0.1334	0.128	0.1002	0.2293

Table 6
Calculation of efficiency scores and ranking of DMUs in FY 2024-25

DMU	PE	ASV	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU1	0.0489	0.5684	0.3433	0.0489	0.1961	9	14	10
DMU2	0.0467	0.6174	0.3325	0.0467	0.1896	16	20	18
DMU3	0.2275	0.4978	0.4476	0.2275	0.3375	1	1	1
DMU4	0.0466	0.6041	0.3350	0.0466	0.1908	15	22	17
DMU5	0.0631	0.5066	0.3635	0.0631	0.2133	3	2	3
DMU6	0.0516	0.5840	0.3415	0.0516	0.1965	11	8	8
DMU7	0.0494	0.4953	0.3591	0.0494	0.2042	4	13	4
DMU8	0.0455	0.6726	0.3217	0.0455	0.1836	21	23	21
DMU9	0.0509	0.5388	0.3504	0.0509	0.2007	7	9	7
DMU10	0.0544	0.3501	0.3975	0.0544	0.2260	2	5	2
DMU11	0.0509	0.5328	0.3517	0.0509	0.2013	6	10	6
DMU12	0.0471	0.5559	0.3449	0.0471	0.1960	8	19	11
DMU13	0.0499	0.5931	0.3388	0.0499	0.1943	13	11	15
DMU14	0.0483	0.7813	0.3049	0.0483	0.1766	23	17	23
DMU15	0.0443	0.7783	0.3033	0.0443	0.1738	25	25	25
DMU16	0.0621	0.7161	0.3224	0.0621	0.1923	20	3	16
DMU17	0.0487	0.6644	0.3247	0.0487	0.1867	18	15	19
DMU18	0.0480	0.5069	0.3558	0.0480	0.2019	5	18	5
DMU19	0.0485	0.5678	0.3432	0.0485	0.1958	10	16	12
DMU20	0.0424	0.7894	0.3006	0.0424	0.1715	26	26	26
DMU21	0.0494	0.6732	0.3235	0.0494	0.1865	19	12	20
DMU22	0.0443	0.7766	0.3036	0.0443	0.1740	24	24	24
DMU23	0.0581	0.6515	0.3318	0.0581	0.1950	17	4	14
DMU24	0.0522	0.6039	0.3378	0.0522	0.1950	14	6	13
DMU25	0.0466	0.7158	0.3147	0.0466	0.1807	22	21	22
DMU26	0.0517	0.5866	0.3410	0.0517	0.1964	12	7	9

Then, we proceed to step 5 (determination of SE scores of the DMUs). With respect to the reference values (identified during the normalization), we find the RSVs of the DMUs using Eq. 12-13. Then, we determine the ASVs (Eq. 14) and subsequently, obtain the SE scores (Eq. 15). To find the IE scores, we set a balance between PE and SE ($\beta = 0.5$). The IE scores for FY 2024-25 are reported in Table 6, while Tables A15-A18 exhibit the same for all other financial years. After obtaining the IE scores, our next job is to determine the CE values (peer evaluation). Using Eq. 17-20, we obtain the CE scores of the DMUs (Tables 6, A15-A18). Subsequently, we use the integration parameter (α) to integrate the IE and CE. We set α = 0.5 to give equal emphasis on internal and external performances. Table 6 reports the calculated OE values to rank the DMUs in FY 2024-25. The final ranking of DMUs for all the years is exhibited in Tables A15-A18. Table 7 summarizes the calculated OE values of the DMUs across the years in the study period.

Table 7
Consolidated year-wise calculation of efficiencies and ranking of DMUs

	FY 20-21		FY 21-22		FY 22-23		FY 23-24		FY 24-25		Aggregate	
DMU	OE	Rank	OE	Rank	OE	Rank	OE	Rank	OE	Rank	BC	Rank
DMU1	0.1909	9	0.2005	4	0.1987	6	0.1970	11	0.1961	10	90	8
DMU2	0.1884	17	0.1915	14	0.1898	13	0.1900	18	0.1896	18	50	18
DMU3	0.1962	4	0.2688	2	0.3370	1	0.3371	1	0.3375	1	121	1
DMU4	0.1905	11	0.1921	11	0.1871	17	0.1891	19	0.1908	17	55	14
DMU5	0.1904	14	0.1941	10	0.1984	7	0.2050	4	0.2133	3	92	5
DMU6	0.1860	18	0.1886	17	0.1859	19	0.1954	15	0.1965	8	53	15
DMU7	0.1936	5	0.1941	9	0.1961	10	0.2006	5	0.2042	4	97	4
DMU8	0.1835	21	0.1818	22	0.1809	22	0.1798	24	0.1836	21	20	22
DMU9	0.1826	24	0.1823	20	0.1842	20	0.1978	7	0.2007	7	52	16
DMU10	0.2275	3	0.2337	3	0.2300	2	0.2296	2	0.2260	2	118	2
DMU11	0.1905	12	0.1958	8	0.1960	11	0.1987	6	0.2013	6	87	9
DMU12	0.1897	15	0.1919	13	0.1918	12	0.1959	13	0.1960	11	66	13
DMU13	0.1924	6	0.1994	6	0.2000	4	0.1977	8	0.1943	15	91	6
DMU14	0.1827	23	0.1831	19	0.1760	26	0.1766	26	0.1766	23	13	24
DMU15	0.1837	20	0.1775	26	0.1782	24	0.1805	23	0.1738	25	12	25
DMU16	0.1915	8	0.1919	12	0.1965	9	0.1958	14	0.1923	16	71	12
DMU17	0.1904	13	0.1905	15	0.1890	14	0.1882	20	0.1867	19	49	19
DMU18	0.2701	1	0.2764	1	0.2150	3	0.2110	3	0.2019	5	117	3
DMU19	0.1920	7	0.1996	5	0.1992	5	0.1974	10	0.1958	12	91	6
DMU20	0.1852	19	0.1839	18	0.1817	21	0.1807	22	0.1715	26	24	21
DMU21	0.1908	10	0.1896	16	0.1883	16	0.1903	17	0.1865	20	51	17
DMU22	0.1834	22	0.1810	23	0.1781	25	0.1792	25	0.1740	24	11	26
DMU23	0.1796	26	0.1806	24	0.1871	18	0.1908	16	0.1950	14	32	20
DMU24	0.1892	16	0.1981	7	0.1976	8	0.1965	12	0.1950	13	74	10
DMU25	0.1799	25	0.1790	25	0.1802	23	0.1817	21	0.1807	22	14	23
DMU26	0.2502	2	0.1819	21	0.1886	15	0.1974	9	0.1964	9	74	10

Figure 2 displays a heatmap showing variations in the OE values of the DMUs across the years. The variations in the ranking positions of the DMUs across the years are shown in Figure 3.

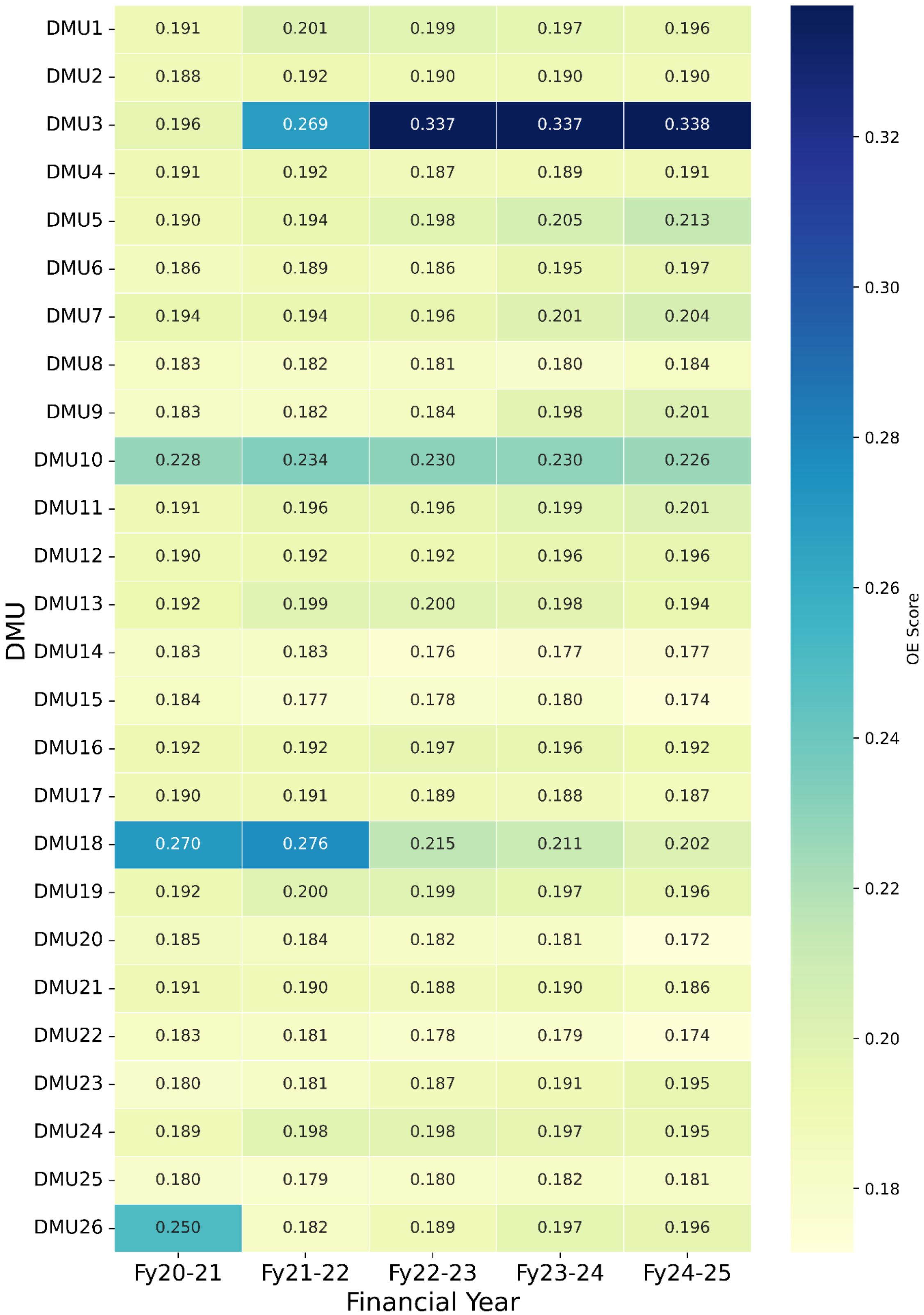

Fig. 2. Variations in the OE scores of the DMUs

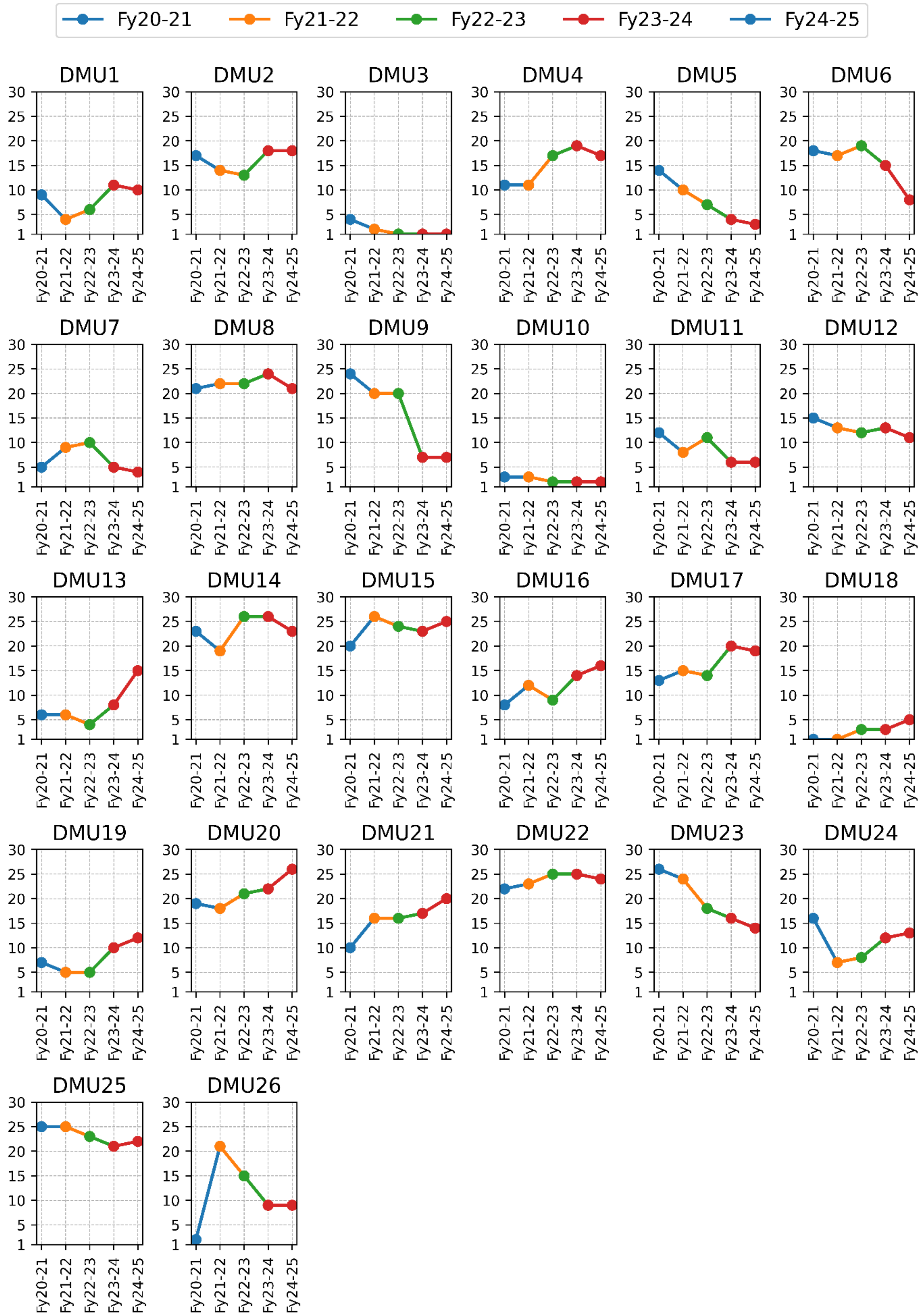

Fig. 3. Variations in the OE scores of the DMUs

6. Validation and robustness analysis

In this section, we present a detailed, multidimensional analysis to validate the outcome and assess the robustness of the modified EATWIOS method.

6.1 Comparison of various MCDM methods

Scholars argue that comparisons of outcomes across various MCDM models are necessary to assess the reliability and generalizability of a specific method [62-64]. This paper compares the outcomes of the modified EATWIOS method with those of other frameworks, including the classical EATWIOS, COPRAS, SAW, RAM, CoCoSo, and MARCOS. We perform Spearman's rank correlation test among the findings to examine their consensus. The statistically significant, high rank-correlation values indicate strong agreement among various methodological frameworks. For instance, Table 8 shows the result of the Spearman's rank correlation test for FY 2024-25. A similar result has been observed for all other years.

Table 8
Result of Spearman's rank correlation test to compare various MCDM methods

Method	EATWIOS	COPRAS	SAW	RAM	CoCoSo	MARCOS
Modified EATWIOS	0.998*	0.965*	0.965*	0.952*	0.968*	0.964*

(Significant at 0.05 level, two-tailed)

6.2 Effect of variations in the performance values

The success of efficiency calculation largely depends on the decision matrix. It is thus worthwhile to examine how variations in the performance values of the DMUs, particularly in the input and output criteria that influence them, affect OE scores and final rankings. This paper introduces a step-wise variation in the performance values of the DMUs under influencing criteria. For example, in FY 2024-25, the calculated weights suggest that C3 (input) and C7 (output) are the influencing criteria. We vary the performance values of the DMUs under C3 and C7 by $\delta = \pm 5\%, \pm 10\%, \pm 50\%, \pm 90\%$and examine their overall impacts on OE scores and the final ranking of DMUs. We then compute the sMAPE value for each such distortion case (between the original and revised OE scores) and Kendall's tau b coefficient (to examine the consensus among the rankings). Table 9 shows that variations in the decision matrix values do not significantly affect the OE scores and the ranking of the DMUs. Figure 4 displays the ranking distributions of the DMUs under various δvalues. A similar observation is made for all other years.

Table 9
Impact of variations in the decision matrix on OE scores and ranking of DMUs

	Distortion cases							
Parameters	δ = +5%	δ = +10%	δ = +50%	δ = -5%	δ = -10%	δ = -50%	δ = +90%	δ = -90%
sMAPE	0.00000	0.00000	0.08109	0.00000	0.00000	0.00001	0.00002	0.00002
Kendall's tau	1.000***	1.000***	0.969***	1.000***	1.000***	1.000***	1.000***	1.000***

Note. * p < .05, ** p < .01, *** p < .001

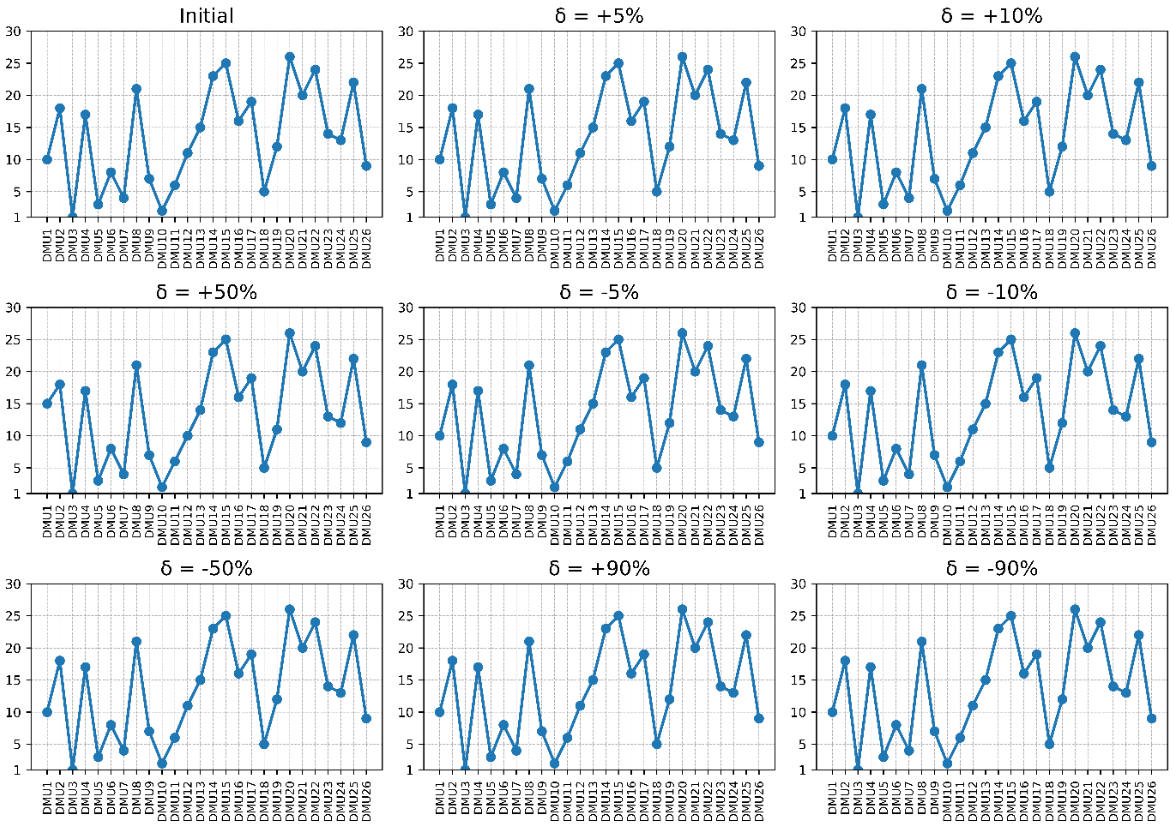

Fig. 4. Ranking distributions of the DMUs under various δ values (FY 2024-25)

6.3 Effect of boundary conditions

This paper uses two integration coefficients, α and β, at two different stages. Both these coefficients can take two boundary values, 0 and 1. Thus, it is worthwhile to examine the effects of the boundary values on the stability of the result. Figure 5 displays the effects of the boundary values of α and β on the ranking of DMUs (FY 2024-25)

It is observed that at the boundary values, DMU 3 always remains at the top position. The bottom three positions (DMU 20, DMU 15, and DMU 22) remain unchanged. We notice that at α = 0 and β = 1, there is a noticeable impact on the final ranking. As evident from Table 10, the Kendall's tau coefficient value is moderate at α = 0 and β = 1. Nevertheless, the rankings across the other boundary conditions (α = 1 and β = 0) remain highly consistent. A similar observation is made for all other years. Thus, overall, we contend that boundary values do not have abrupt impacts on the model stability.

Table 10
Test of consistency of the rankings at various boundary cases with the original

	Boundary cases			
Parameter	α = 0	α = 1	β = 0	β = 1
Kendall's tau	0.520***	0.908***	0.908***	0.520***

Note. * p < .05, ** p < .01, *** p < .001

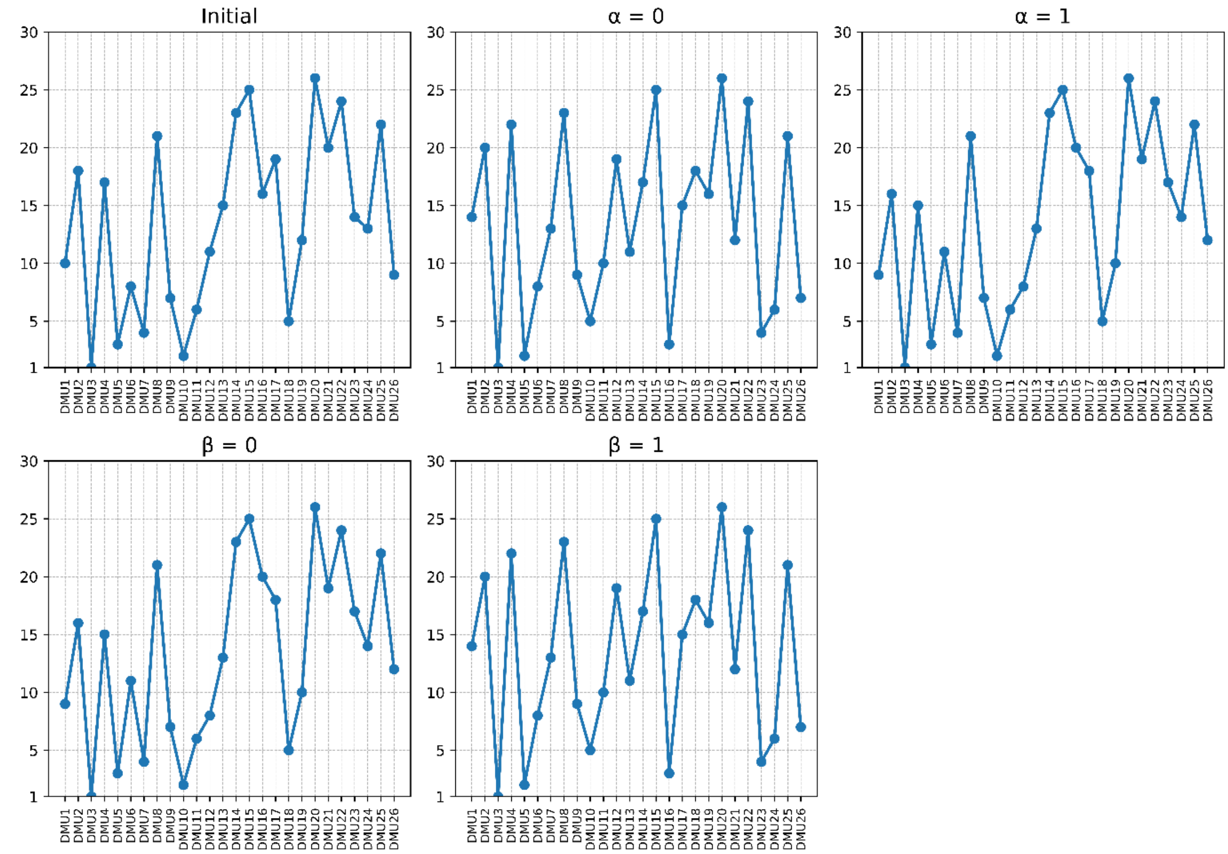

Fig. 5. Ranking distribution of the DMUs at various boundary values (FY 2024-25)

6.4 Effect of variations in α and β coefficients

In addition to the boundary values, we vary α and β over the range [0, 1]. For each value, we compute the OE score and rank the DMUs. For example, in FY 2024-25, the plots of the DMUs' rankings at various α and β values (Figures 6 and 7) show no significant deviation. The result of Spearman's rank correlation test (Table 11) confirms that the ranking of DMUs across various α and β values maintains a statistically significant, high correlation with the initial order. A similar observation is made for all other years.

Table 11
Test of consistency of the rankings at various α and β values with the original

Cases	α = 0.1	α = 0.2	α = 0.3	α = 0.4	α = 0.6	α = 0.7	α = 0.8	α = 0.9
Spearman's rho	0.852**	0.889**	0.952**	0.982**	0.990**	0.986**	0.983**	0.981**
Cases	β= 0.1	β= 0.2	β= 0.3	β= 0.4	β = 0.6	β = 0.7	β = 0.8	β = 0.9
Spearman's rho	0.981**	0.983**	0.986**	0.990**	0.982**	0.952**	0.889**	0.852**

Note. * p < .05, ** p < .01

6.5 Effect of variations in criteria weights

The variation in the criteria weights is a notable concern affecting the stability of the MCDM model. Scholars (for instance, [65-67]) have extensively assessed the impact of variations in criterion weights on MCDM rankings. We change the weights of the criteria and recompute the OE scores to rank the DMUs.

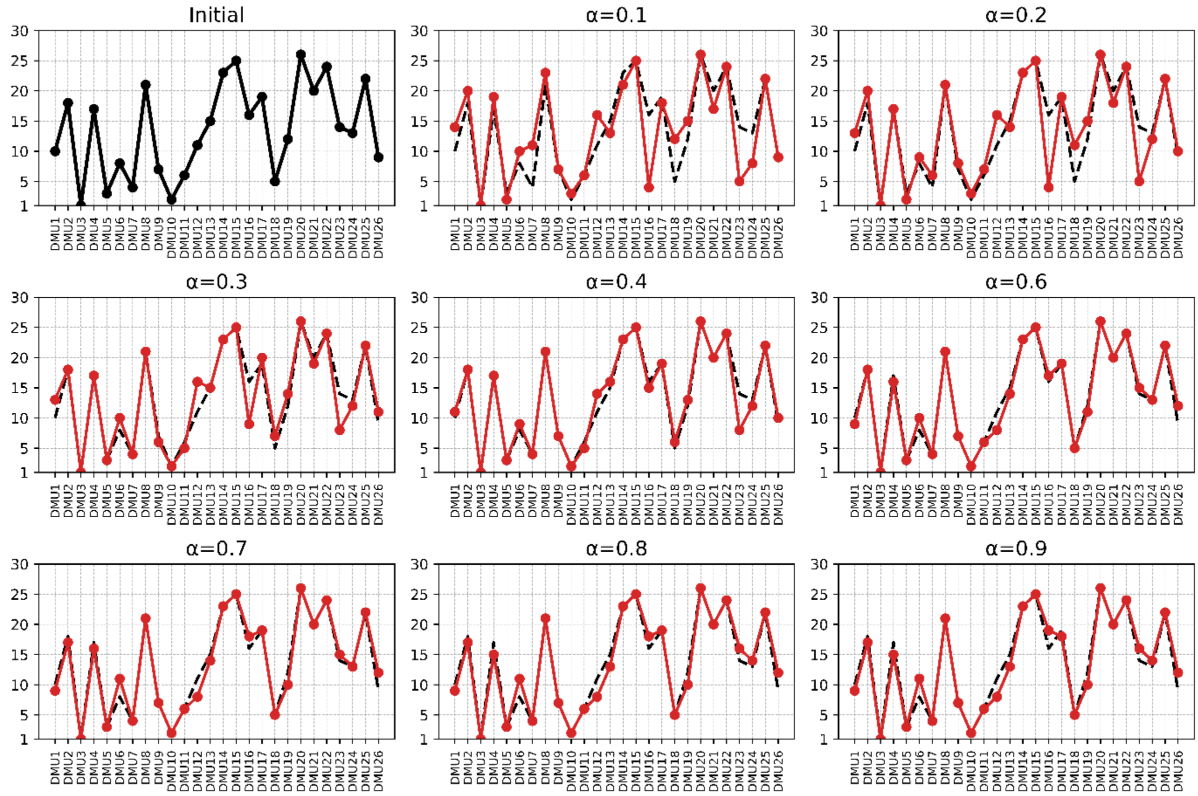

Fig. 6. Effect of variations in α values on final ranking (FY 2024-25)

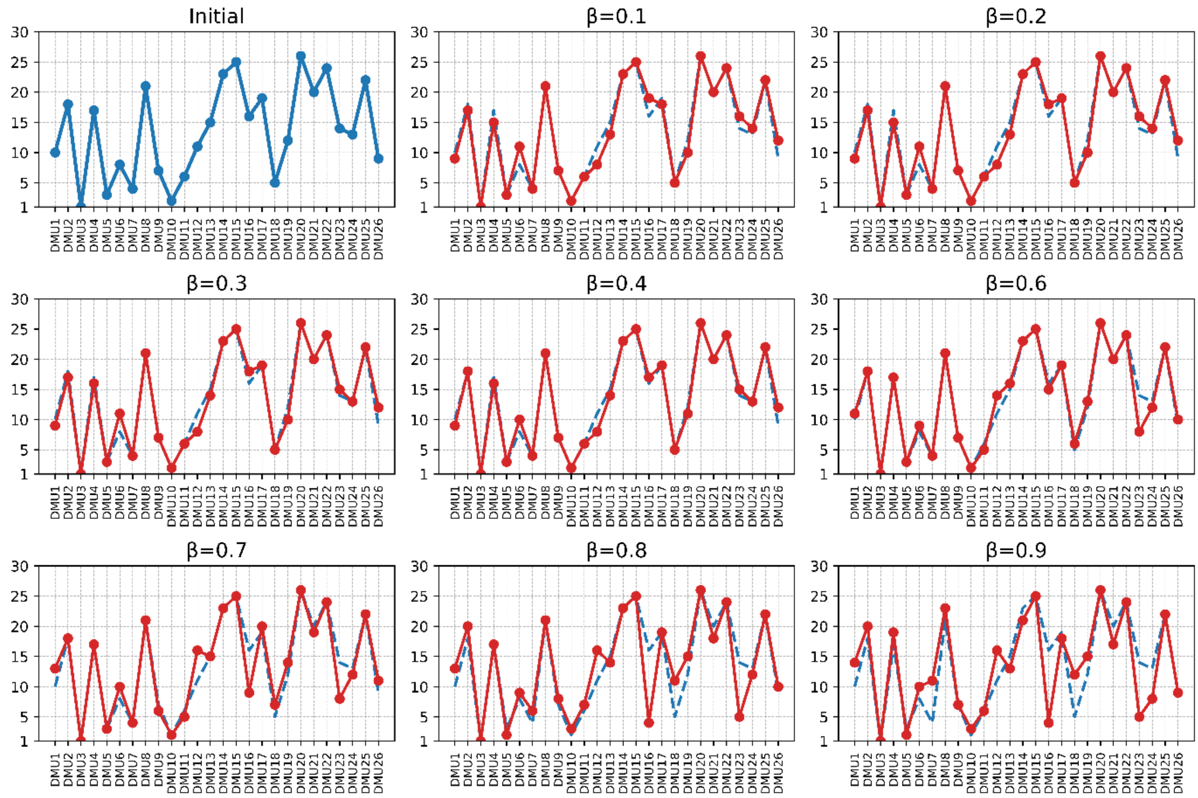

Fig. 8. Effect of variations in β values on final ranking (FY 2024-25)

For instance, in FY 2024-25, we vary the weights of C3 and C7 by 10% at each step and rank the DMUs. Figure 8 shows that DMUs maintain absolute consistency in their rankings despite changes in the criteria weights in FY 2024-25. A similar pattern is observed for all other years. Thus, we contend that variations in the weights of criteria do not significantly affect the final ranking and the model is stable.

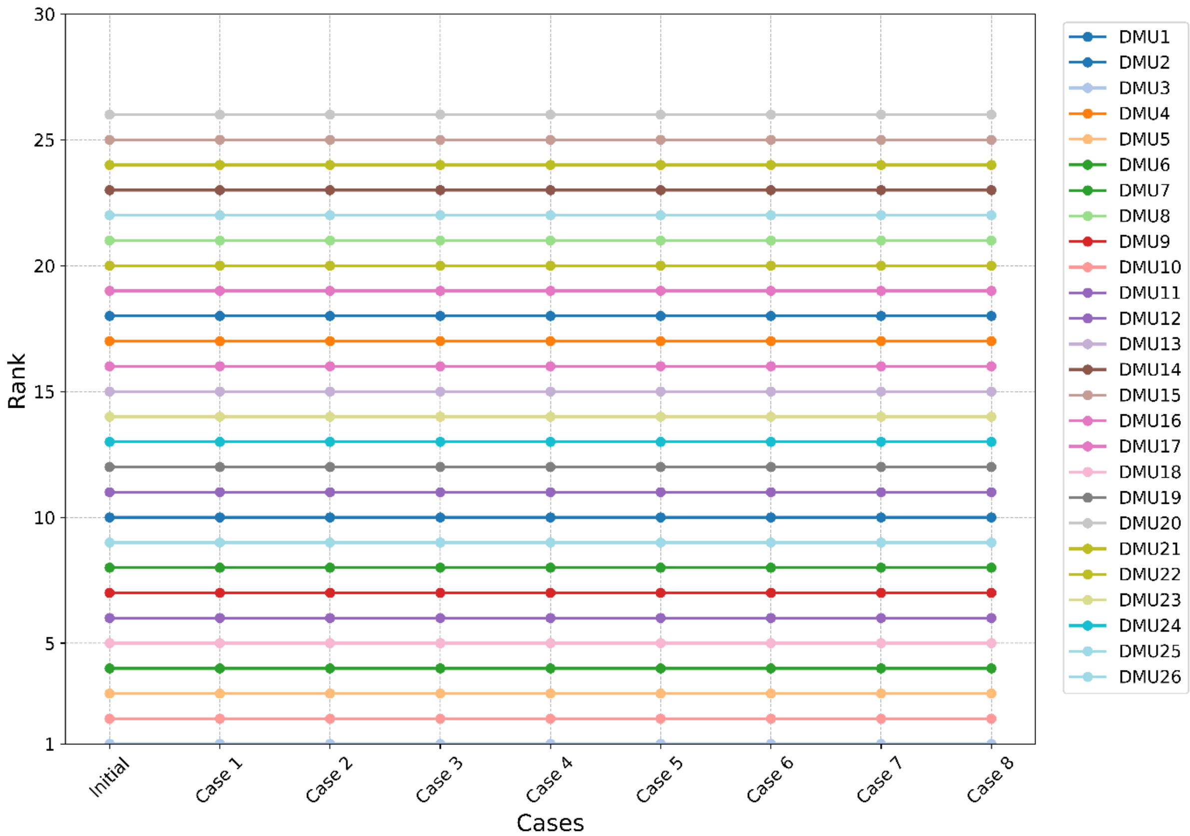

Fig. 8. Effect of variations in criteria weights on final ranking (FY 2024-25)

7. Discussion

This research adds to the existing body of literature on banking efficiency by offering an updated EATWIOS approach. It combines objective weighting, slack-based inefficiency analysis, and benchmarking into a single, cohesive analytical framework. The findings indicate that banking efficiency is not only dependent on increasing size and improving banking operations but is also dependent on the interplay of capital strength, asset quality, and financing cost structures. It has been well established in previous literature that capital structure and asset quality are highly significant in determining bank risk-taking, stability, and efficiency [1, 7-8]. In this study, the traditional approach, in which financial stability variables are considered as external variables, has been expanded by incorporating them into the efficiency framework.

According to empirical findings, banks vary greatly in their efficiency levels, but only a few manage to stay ahead over time. This is not a new phenomenon; earlier research into ownership, mergers, and day-to-day banking operations have also revealed similar levels of efficiency in banks [10-11, 16]. When we analyze the rankings in general, we find that the banks that rank high do not do so in a single area. Rather, they excel in all areas: deposit growth, capital adequacy, lending, and risk management. In other words, efficiency in banks is not about being the best at one single task but about being good at all tasks. This can also be seen when we look at the general consensus in the literature that banking involves multifaceted issues like efficiency, stability, and sustainability [27, 35].

From the results, it is clear that the addition of slack-based efficiency metrics improves the ability of the model to differentiate performance, which is more than what traditional radial efficiency techniques can achieve. Traditional models for efficiency often fail to identify non-proportional inefficiency unless the slack structure is considered [14, 35]. The new model is able to identify hidden inefficiencies that may not be apparent if one is only concerned with proportionate gains. This is a clear indication that, in the absence of information on non-proportional inefficiency, radial efficiency may overestimate performance. With the ability to measure deviation through the use of slack, the model has enhanced diagnostic capabilities.

One important thing that comes to light is that peer review is incorporated in the efficiency assessment process. The traditional models compare banks with their ideal and top-performing benchmarks, but by incorporating peer review, as proposed in this study, efficiency assessment depends on comparisons with peer banks. This is in line with recent studies that have emphasized hybrid and benchmarking-based performance evaluation models for banks [44-45, 48]. The double dimension of internal and external efficiency not only makes it easy to understand but is in line with modern decision support techniques that incorporate multiple evaluative dimensions [46,49,68,69].

The robustness analysis improves the robustness of the framework. We identify robust rank correlations between the modified EATWIOS technique and various MCDM approaches. This confirms the methodological robustness of the proposed technique. Past studies emphasize that cross-method validations are critical in order to verify the consistency and generality of MCDM models [54-55]. Our robustness analysis indicates that minor variations in the decision matrix values and criteria weights do not affect the order of the rankings, thus proving the robustness of the proposed technique. This is in line with previous studies that emphasize the need to test the robustness of hybrid MCDM models [52-53].

From this research, it is clear that the integration of objective weighing techniques and efficiency measurement frameworks can greatly enhance the robustness of the assessment. By applying the MPSI approach to determine the weights of the criteria based on the extent of performance variability, the subjective nature associated with expert-based weighting can be eliminated. This is in line with previous research that recommended the use of objective weighting techniques to improve the reliability of performance assessment models [50-51].

7.1 Research implications

From a management point of view, it is obvious that banks seeking to improve efficiency need to focus more on balanced financial strategies, as opposed to growth maximization. The findings suggest that banks can improve efficiency by raising asset quality and reducing financial costs, just as much as they can by increasing deposits or improving loans.

In addition, regulatory systems that emphasize capital adequacy and asset quality can improve banking efficiency as well. The cost of capital and asset quality are structural drivers of efficiency, and therefore, focusing on financial systems can improve efficiency indirectly.

The newly developed Modified EATWIOS framework extends the efficiency study by using a hybrid assessment approach, which includes radial efficiency, non-radial inefficiency, and peer group competitiveness in a single model. This provides a more holistic study, enhancing the theory and application of efficiency evaluation in complex financial systems. It is, therefore, an important tool for efficiency analysis for financial institutions, as well as for policymakers and practitioners.

7.2 Limitations and future scopes

Despite the methodological weight and insightful results, this research comes with caveats that provide a roadmap for future studies.

The empirical study is confined to the Indian commercial bank's dataset and a narrow set of financial variables. Although the selected variables account for the major dimensions of banking efficiency: capital management, asset quality, and funding costs—banking efficiency is, by definition, a multi-dimensional phenomenon. It can also be influenced by factors such as governance quality, technology adoption, risk culture, and macroeconomic factors. Future studies could extend the model by incorporating ESG factors, digital banking adoption, or financial inclusion criteria to provide a more comprehensive efficiency perspective.

Although the modified EATWIOS approach enhances the discriminative capability by incorporating slack efficiency and peer benchmarking, the model retains its deterministic nature, like most MCDM-based efficiency models. Consequently, the model does not account for uncertainty, stochastic changes, or measurement errors in financial variables. Future studies could address this limitation by incorporating fuzzy set theory, rough numbers, or probabilistic models to enhance robustness against uncertainty.

The study adopts objective weighting based on the MPSI approach. Although this approach minimizes subjective bias, a combination of objective and subjective weighting methods (e.g., AHP or Best-Worst Method) could provide a more balanced representation of administrative preferences. Hybrid weighting models could also enhance the applicability of the approach.

The study is confined to static annual efficiency analysis. Future studies could extend the analysis to dynamic efficiency analysis by incorporating Malmquist productivity analysis or window analysis to analyze efficiency changes over time.

From a methodological perspective, future studies could investigate the integration of the modified EATWIOS approach with machine learning or Explainable AI models to enhance the predictive capability and interpretability of the underlying efficiency drivers. Such an extension would enhance the applicability of hybrid efficiency-decision models in financial performance analysis.

8. Conclusion

This research proposes a new approach to EATWIOS by modifying it to evaluate the efficiency of 26 DMUs, consisting of 12 public banks and 14 private banks. We combine the calculation of efficiency using the Slack approach and peer assessment with the conventional EATWIOS approach to provide a more comprehensive and detailed performance analysis. The weights of the criteria are assigned using the MPSI approach. Through the analysis of 26 banks over several periods, particularly in terms of asset quality and capital management, we conclude that efficiency is strongly linked to financial stability and risk management, rather than mere scale and growth. Our robustness and sensitivity analysis indicates that the model is stable and reliable, indicating that it can be used as a reliable decision-making tool for performance evaluation. In terms of methodology, this research demonstrates a good integration of objective weighting with distance-based efficiency approaches to enhance the reliability of analysis. For bank managers, this research indicates that improving efficiency by optimizing capital management and improving risk management is essential; for policymakers, this research indicates that stability-focused performance evaluation is possible. The proposed approach provides a flexible and robust method for multidimensional efficiency analysis and provides new avenues for hybrid efficiency modeling in financial performance analysis.

Appendix A

Table A1
Decision matrix for FY 2020-21

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	966996.9	81227.22	1034.27	714975.8	1155364.78	0.8327	0.9691
DMU2	627113.6	47882.64	3276.92	370566.1	725856.43	0.8261	0.9665
DMU3	174005.6	13760.89	6560.16	104145.2	196682.24	0.8836	0.9752
DMU4	1010875	82642.49	1646.74	652719.1	1159810.54	0.8566	0.9618
DMU5	329973	27873.1	5875.56	160815.9	370089.57	0.8545	0.9663
DMU6	538071.1	43437.92	1129.37	369294.4	624376.58	0.8319	0.9642
DMU7	240288.3	21674.61	16436.99	131172.7	274010.36	0.8815	0.9423
DMU8	96108.17	9396.89	4052.67	61333.55	110568.36	0.8230	0.9596
DMU9	1106332	91483.87	2095.54	684021.9	1261767.99	0.8179	0.9427
DMU10	3681277	316135.2	892.46	2475522	4543830.89	0.8574	0.9850
DMU11	205919.4	18542.22	9918.34	111401.5	253336.11	0.8450	0.9606
DMU12	923805.3	76787.27	6406.84	598803	1074972.9	0.8371	0.9538
DMU13	707306.1	71228.76	612.75	671446	996160.46	0.7449	0.9894
DMU14	44537.37	4249.11	73.88	37143.47	53311.69	0.7924	0.9703
DMU15	29703.86	3759.48	310.54	25801.32	39644.48	0.7753	0.9769
DMU16	11711.9	1321.78	253.01	6836.73	13098.01	0.8494	0.9524
DMU17	172644.5	15398.65	399.23	133140.8	201696.73	0.7967	0.9881
DMU18	1335060	120304.4	551.28	1140893	1746870.53	0.8255	0.9960
DMU19	932522.2	81263.38	1383.2	772238.4	1233580.54	0.7201	0.9876
DMU20	256205	32189.55	773.37	213351.8	363328.03	0.6306	0.9931
DMU21	108061.2	9857.14	71.35	67076.15	120291.94	0.8668	0.9705
DMU22	75654.86	7354.92	310.89	52282.36	85729.28	0.8203	0.9681
DMU23	63278.43	7000.06	159.86	50363.5	74722.58	0.7705	0.9659
DMU24	280100.1	28323.87	990.92	223670.2	383633.65	0.7628	0.9879
DMU25	82710.56	8771.26	209.27	58323.7	94249.7	0.8366	0.9529
DMU26	162946.7	25441.78	5010.98	167399.4	273542.77	0.9269	0.9412

Table A2
Decision matrix for FY 2021-22

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	1045939	79566.35	1034.27	784458.7	1277999.82	0.9591	0.9828
DMU2	627896	47709.98	4103.57	428211.8	734614.02	0.9541	0.9766
DMU3	202294.3	14247	6730.5	133190.4	230623.78	0.9621	0.9903
DMU4	1086409	82407.24	1814.13	719662.2	1228104.87	0.9549	0.9735
DMU5	342692	28161.47	8680.94	172136.8	387291.26	0.9555	0.9773
DMU6	593617.8	43251.83	1245.44	395593.6	672645.21	0.9548	0.9735
DMU7	262158.9	21417.62	18902.41	148374.2	299377.18	0.9552	0.9603
DMU8	102137	8792.32	6777.79	64086.94	121157.95	0.9436	0.9726
DMU9	1146218	86609.31	2202.2	740209.8	1315975.35	0.9520	0.9520
DMU10	4051534	338750.9	892.46	2756259	4998094.61	0.9591	0.9898
DMU11	224072.9	18192.08	11955.96	122834.9	267784.03	0.9572	0.9730

Table A2
Continued

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU12	1032393	75879.16	6834.75	669363.7	1190790.77	0.9557	0.9632
DMU13	821971.6	79449.35	613.95	750331.7	1175625.24	0.9520	0.9933
DMU14	47689.67	4800.48	73.96	41403.48	61530.91	0.9490	0.9705
DMU15	34691.68	4059.76	310.98	29164.4	44844	0.9368	0.9803
DMU16	12402.89	1309.36	253.01	8192.31	13800.16	0.9500	0.9715
DMU17	181700.6	16120.65	420.51	146318.8	221306.54	0.9497	0.9904
DMU18	1559217	127428.3	554.55	1378024	2068535.05	0.9579	0.9968
DMU19	1064572	90438.54	1389.76	891470.6	1414871.96	0.9509	0.9919
DMU20	293681.4	34664.14	774.66	240264.3	402339.38	0.9323	0.9936
DMU21	114710.4	11038.02	93.29	70662.7	130602.42	0.9585	0.9751
DMU22	80386.84	7311.42	311.18	58165.71	91673.61	0.9468	0.9758
DMU23	68486.02	6452.06	160	54661.2	80071.33	0.9454	0.9769
DMU24	311684.1	31531.57	992.33	271253.6	429615.8	0.9548	0.9936
DMU25	89142.1	8511.43	209.27	60325.34	100206.17	0.9471	0.9703
DMU26	197191.7	25393.12	5010.99	181655.5	318220.22	0.9550	0.9547

Table A3
Decision matrix for FY 2022-23

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	1203688	96781.25	1034.27	948051.6	1458561.53	0.9575	0.9911
DMU2	669585.8	54497.05	4103.57	492760.7	815555.61	0.9566	0.9834
DMU3	234082.7	15709.11	6730.5	173058.9	267664.28	0.9627	0.9975
DMU4	1179219	98768.27	1814.13	850276.1	1345732.22	0.9529	0.9827
DMU5	359296.5	31071.47	8680.94	207245.5	406956.63	0.9576	0.9910
DMU6	621165.8	48113.2	1245.44	454551.1	711526.14	0.9560	0.9817
DMU7	260883.3	23783.98	18902.41	182575.2	313733.98	0.9551	0.9823
DMU8	109665.5	9986.71	6777.79	77360.93	136537.4	0.9482	0.9816
DMU9	1281163	99943.7	2202.2	857957.7	1463080.62	0.9563	0.9728
DMU10	4423778	382312.6	892.46	3215786	5528044.56	0.9581	0.9933
DMU11	249337.7	21609.58	11955.96	155963.6	300863	0.9566	0.9871
DMU12	1117716	92281.53	6834.75	773090.4	1284343.98	0.9545	0.9830
DMU13	946945.2	95221.69	615.37	876479.7	1317743.85	0.9540	0.9959
DMU14	52397.86	5572.95	74.04	44162.7	66594.56	0.9473	0.9764
DMU15	41238.9	5009.98	311.5	34449.31	52425.27	0.9409	0.9896
DMU16	13351.65	1449.81	253.01	9502.95	15135.81	0.9530	0.9884
DMU17	213386	18825.58	423.24	176023.7	260791.24	0.9515	0.9931
DMU18	1883395	166693.7	557.97	1612490	2466081.47	0.9564	0.9973
DMU19	1180841	111628.8	1396.56	1048409	1588345.86	0.9527	0.9949
DMU20	336438.1	41234.92	775.9	290020.3	458202.58	0.9380	0.9941
DMU21	122037.7	11599.11	103.15	82471.95	145962.27	0.9596	0.9838
DMU22	87368.01	7983.4	312.36	61058.69	99160.97	0.9485	0.9830

Table A3
Continued

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU23	76637.58	7123.35	160.41	63134.14	90297.84	0.9503	0.9926
DMU24	363096.1	40365.95	993.28	319861.2	489862.47	0.9547	0.9963
DMU25	91651.35	9133.4	209.27	70210.34	108023.44	0.9529	0.9814
DMU26	217501.9	29638.1	5750.96	203954.6	354786.14	0.9484	0.9917

Table A4
Decision matrix for FY 2023-24

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	1335136	121501.7	1034.27	1073680	1585797.08	0.9347	0.9932
DMU2	737920.2	66954.8	4552.67	568678.9	914240.09	0.9352	0.9878
DMU3	270747.2	19861.06	7081.37	202050	307150.77	0.9495	0.9980
DMU4	1312367	123534.6	1814.13	949167.7	1491540.73	0.9328	0.9873
DMU5	385011.3	37316.44	8680.94	247922	447517.16	0.9424	0.9957
DMU6	688000	60041.69	1346.96	517802.5	793735.69	0.9356	0.9943
DMU7	285905.4	30992.48	18902.41	218769.3	352033.6	0.9400	0.9877
DMU8	119409.6	13134.3	6777.79	83437.66	147744	0.9225	0.9837
DMU9	1369713	124593.5	2202.2	945492.2	1563223.02	0.9371	0.9927
DMU10	4916077	498272.6	892.46	3727611	6192790.23	0.9404	0.9943
DMU11	263129.8	27212.85	11955.96	182182.9	323691.45	0.9396	0.9911
DMU12	1221528	110316.4	7633.6	877878.2	1394745.33	0.9336	0.9897
DMU13	1068641	127233.2	617.31	986703.6	1477892.9	0.9265	0.9966
DMU14	55656.65	5980.84	74.07	46772.19	70825.88	0.9241	0.9803
DMU15	49353.03	6322.61	312.8	40971.01	63107.2	0.9216	0.9889
DMU16	14290.31	1785.23	253.01	10161.9	15963.41	0.9359	0.9875
DMU17	252534	25862.26	487.07	211107.9	308827.63	0.9255	0.9940
DMU18	2379786	272251.9	759.69	2516193	3623225.45	0.9308	0.9967
DMU19	1412825	144214.2	1404.46	1212182	1876488.02	0.9248	0.9955
DMU20	384792.9	53359.36	778.32	344043.6	515826.43	0.8998	0.9943
DMU21	134776.3	13570.05	110.12	93825.36	154526.58	0.9376	0.9921
DMU22	97988.23	9786.33	377.27	72405.49	116205.24	0.9303	0.9842
DMU23	89112.72	9885.17	160.88	73667.48	105587.37	0.9254	0.9960
DMU24	448953.8	51934.68	993.96	376269.1	600923.76	0.9319	0.9966
DMU25	101920.3	11081.12	261.59	78453.26	117647.08	0.9340	0.9854
DMU26	266372.2	36542.05	5753.58	228992.9	405492.99	0.9383	0.9942

Table A5
Decision matrix for FY 2024-25

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	1472035	133699.5	1034.27	1219834	1781247.31	0.9431	0.9942
DMU2	816541.5	79339.9	4552.67	653674	1044460.49	0.9414	0.9918
DMU3	307142.6	24316.88	7691.56	237841.7	369272.34	0.9518	0.9982

Table A5
Continued

	Input					Output	
DMU	C1	C2	C3	C4	C5	C6	C7
DMU4	1456883	137277.7	1814.13	1065244	1682849.6	0.9388	0.9930
DMU5	412697.2	41908.68	9051.4	286116.7	480167.58	0.9470	0.9981
DMU6	737153.6	66707.66	1346.96	571071.2	874654.17	0.9427	0.9963
DMU7	311938.8	31946.42	19256.59	247870.6	395014.95	0.9430	0.9945
DMU8	129774	13996.8	7095.59	97789.2	161907.46	0.9369	0.9904
DMU9	1566623	142176.3	2298.59	1086841	1820357.34	0.9434	0.9960
DMU10	5382190	525118.7	892.46	4194694	6691035.91	0.9435	0.9953
DMU11	293542.2	31192.38	12539.56	215281.1	362481.1	0.9451	0.9950
DMU12	1309750	120243.3	7633.6	956969	1502886.28	0.9395	0.9937
DMU13	1172952	139930.9	619.47	1056367	1611217.92	0.9353	0.9965
DMU14	63525.96	7276.69	74.1	53245.08	77623.22	0.9329	0.9875
DMU15	60030.94	7810.06	314.29	51077.51	76892.77	0.9292	0.9888
DMU16	16013.45	1900.71	394.7	12016.62	17940.81	0.9408	0.9901
DMU17	283647.5	30698.97	491.17	236537.6	349004.82	0.9328	0.9956
DMU18	2714715	307706.2	765.22	2649738	3917685.68	0.9344	0.9957
DMU19	1610348	163392.7	1424.39	1365592	2124067.25	0.9356	0.9958
DMU20	411078.1	62293.31	779.05	347339.9	555227.28	0.9167	0.9905
DMU21	148569.5	14487.61	110.12	104305.1	169468.46	0.9441	0.9921
DMU22	104807.5	11089.91	377.95	77677.09	121113.41	0.9349	0.9869
DMU23	102078	34937.99	161.02	84004.54	119537.76	0.9331	0.9980
DMU24	499055.1	60105.74	994.11	426909.2	694476.51	0.9399	0.9969
DMU25	107525.6	11937.51	261.63	85988.87	124867.9	0.9379	0.9908
DMU26	284525.1	40775.41	6270.82	247836.9	423422.3	0.9372	0.9970

Table A6
Normalized decision matrix (FY 2020-21)

Reference	3681277.08	1321.78	16436.99	2475521.77	4543830.89	0.0731	0.0040
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.2603	0.7462	0.0588	0.2868	0.2521	0.6820	0.5091
DMU2	0.1677	0.8521	0.1959	0.1473	0.1573	0.6596	0.4617
DMU3	0.0442	0.9605	0.3965	0.0394	0.0405	0.8540	0.6204
DMU4	0.2723	0.7417	0.0963	0.2616	0.2531	0.7627	0.3759
DMU5	0.0867	0.9157	0.3547	0.0624	0.0788	0.7556	0.4580
DMU6	0.1434	0.8662	0.0646	0.1468	0.1349	0.6792	0.4197
DMU7	0.0623	0.9353	1.0000	0.0504	0.0576	0.8467	0.0201
DMU8	0.0230	0.9743	0.2433	0.0221	0.0215	0.6493	0.3358
DMU9	0.2983	0.7136	0.1237	0.2743	0.2756	0.6319	0.0274
DMU10	1.0000	0.0000	0.0502	1.0000	1.0000	0.7654	0.7993
DMU11	0.0529	0.9453	0.6017	0.0424	0.0530	0.7234	0.3540
DMU12	0.2486	0.7603	0.3871	0.2398	0.2344	0.6967	0.2299
DMU13	0.1896	0.7779	0.0331	0.2692	0.2170	0.3857	0.8796
DMU14	0.0089	0.9907	0.0002	0.0123	0.0089	0.5461	0.5310
DMU15	0.0049	0.9923	0.0146	0.0077	0.0059	0.4881	0.6515

Table A6
Continued

Reference	3681277.08	1321.78	16436.99	2475521.77	4543830.89	0.0731	0.0040
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU16	0.0000	1.0000	0.0111	0.0000	0.0000	0.7384	0.2044
DMU17	0.0439	0.9553	0.0200	0.0512	0.0416	0.5605	0.8558
DMU18	0.3606	0.6221	0.0293	0.4594	0.3827	0.6576	1.0000
DMU19	0.2509	0.7461	0.0802	0.3100	0.2694	0.3018	0.8467
DMU20	0.0666	0.9019	0.0429	0.0837	0.0773	0.0000	0.9471
DMU21	0.0263	0.9729	0.0000	0.0244	0.0237	0.7970	0.5347
DMU22	0.0174	0.9808	0.0146	0.0184	0.0160	0.6402	0.4909
DMU23	0.0141	0.9820	0.0054	0.0176	0.0136	0.4721	0.4507
DMU24	0.0731	0.9142	0.0562	0.0878	0.0818	0.4462	0.8522
DMU25	0.0193	0.9763	0.0084	0.0209	0.0179	0.6952	0.2135
DMU26	0.0412	0.9234	0.3018	0.0650	0.0575	1.0000	0.0000

Table A7
Normalized decision matrix (FY 2021-22)

Reference	4051534.13	1309.36	18902.41	2756259.49	4998094.61	0.0379	0.0032
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.2559	0.7681	0.0510	0.2825	0.2536	0.8987	0.6875
DMU2	0.1524	0.8625	0.2140	0.1528	0.1446	0.7334	0.5491
DMU3	0.0470	0.9617	0.3535	0.0455	0.0435	1.0000	0.8549
DMU4	0.2659	0.7597	0.0924	0.2589	0.2436	0.7604	0.4799
DMU5	0.0818	0.9204	0.4571	0.0597	0.0749	0.7793	0.5647
DMU6	0.1439	0.8757	0.0622	0.1410	0.1322	0.7568	0.4799
DMU7	0.0618	0.9404	1.0000	0.0510	0.0573	0.7691	0.1853
DMU8	0.0222	0.9778	0.3560	0.0203	0.0215	0.3805	0.4598
DMU9	0.2807	0.7472	0.1130	0.2664	0.2613	0.6618	0.0000
DMU10	1.0000	0.0000	0.0435	1.0000	1.0000	0.9000	0.8438
DMU11	0.0524	0.9500	0.6311	0.0417	0.0510	0.8375	0.4688
DMU12	0.2525	0.7790	0.3591	0.2406	0.2361	0.7870	0.2500
DMU13	0.2004	0.7684	0.0287	0.2701	0.2331	0.6602	0.9219
DMU14	0.0087	0.9897	0.0000	0.0121	0.0096	0.5597	0.4129
DMU15	0.0055	0.9918	0.0126	0.0076	0.0062	0.1498	0.6317
DMU16	0.0000	1.0000	0.0095	0.0000	0.0000	0.5939	0.4353
DMU17	0.0419	0.9561	0.0184	0.0503	0.0416	0.5832	0.8571
DMU18	0.3830	0.6262	0.0255	0.4985	0.4122	0.8586	1.0000
DMU19	0.2605	0.7359	0.0699	0.3214	0.2811	0.6256	0.8906
DMU20	0.0696	0.9012	0.0372	0.0844	0.0780	0.0000	0.9286
DMU21	0.0253	0.9712	0.0010	0.0227	0.0234	0.8792	0.5156
DMU22	0.0168	0.9822	0.0126	0.0182	0.0156	0.4868	0.5313
DMU23	0.0139	0.9848	0.0046	0.0169	0.0133	0.4403	0.5558
DMU24	0.0741	0.9104	0.0488	0.0957	0.0834	0.7555	0.9286
DMU25	0.0190	0.9787	0.0072	0.0190	0.0173	0.4957	0.4085
DMU26	0.0457	0.9286	0.2622	0.0631	0.0611	0.7616	0.0603

Table A8
Normalized decision matrix (FY 2022-23)

Reference	4423777.77	1449.81	18902.41	3215786.47	5528044.56	0.0373	0.0025
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.2699	0.7497	0.0510	0.2927	0.2618	0.7880	0.7409
DMU2	0.1488	0.8607	0.2140	0.1507	0.1452	0.7535	0.4291
DMU3	0.0500	0.9626	0.3535	0.0510	0.0458	1.0000	1.0000
DMU4	0.2643	0.7445	0.0924	0.2622	0.2414	0.6018	0.4008
DMU5	0.0784	0.9222	0.4571	0.0617	0.0711	0.7918	0.7368
DMU6	0.1378	0.8775	0.0622	0.1388	0.1263	0.7288	0.3603
DMU7	0.0561	0.9414	1.0000	0.0540	0.0542	0.6917	0.3846
DMU8	0.0218	0.9776	0.3560	0.0212	0.0220	0.4136	0.3563
DMU9	0.2875	0.7414	0.1130	0.2646	0.2626	0.7402	0.0000
DMU10	1.0000	0.0000	0.0435	1.0000	1.0000	0.8146	0.8300
DMU11	0.0535	0.9471	0.6311	0.0457	0.0518	0.7527	0.5789
DMU12	0.2504	0.7615	0.3591	0.2382	0.2302	0.6658	0.4130
DMU13	0.2117	0.7538	0.0288	0.2704	0.2363	0.6472	0.9352
DMU14	0.0089	0.9892	0.0000	0.0108	0.0093	0.3773	0.1457
DMU15	0.0063	0.9907	0.0126	0.0078	0.0068	0.1187	0.6802
DMU16	0.0000	1.0000	0.0095	0.0000	0.0000	0.6088	0.6316
DMU17	0.0454	0.9544	0.0185	0.0519	0.0446	0.5463	0.8219
DMU18	0.4240	0.5661	0.0257	0.5000	0.4446	0.7442	0.9919
DMU19	0.2647	0.7107	0.0702	0.3240	0.2854	0.5967	0.8947
DMU20	0.0733	0.8955	0.0373	0.0875	0.0804	0.0000	0.8623
DMU21	0.0246	0.9734	0.0015	0.0228	0.0237	0.8736	0.4453
DMU22	0.0168	0.9828	0.0127	0.0161	0.0152	0.4258	0.4130
DMU23	0.0143	0.9851	0.0046	0.0167	0.0136	0.4984	0.8016
DMU24	0.0793	0.8978	0.0488	0.0968	0.0861	0.6752	0.9514
DMU25	0.0178	0.9798	0.0072	0.0189	0.0168	0.6040	0.3482
DMU26	0.0463	0.9260	0.3015	0.0606	0.0616	0.4203	0.7652

Table A9
Normalized decision matrix (FY 2023-24)

Reference	4916076.76	1785.23	18902.41	3727611.32	6192790.23	0.0505	0.0020
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.2695	0.7589	0.0510	0.2861	0.2541	0.7024	0.7288
DMU2	0.1476	0.8687	0.2379	0.1502	0.1454	0.7137	0.4237
DMU3	0.0523	0.9636	0.3722	0.0516	0.0471	1.0000	1.0000
DMU4	0.2648	0.7548	0.0924	0.2526	0.2389	0.6650	0.3955
DMU5	0.0756	0.9284	0.4571	0.0640	0.0699	0.8577	0.8701
DMU6	0.1374	0.8827	0.0676	0.1366	0.1259	0.7205	0.7910
DMU7	0.0554	0.9412	1.0000	0.0561	0.0544	0.8102	0.4181
DMU8	0.0214	0.9771	0.3560	0.0197	0.0213	0.4568	0.1921
DMU9	0.2765	0.7526	0.1130	0.2516	0.2505	0.7516	0.7006
DMU10	1.0000	0.0000	0.0435	1.0000	1.0000	0.8166	0.7910
DMU11	0.0508	0.9488	0.6311	0.0463	0.0498	0.8022	0.6102
DMU12	0.2463	0.7814	0.4015	0.2334	0.2232	0.6813	0.5311

Table A9
Continued

Reference	4916076.76	1785.23	18902.41	3727611.32	6192790.23	0.0505	0.0020
Criteria/DMU	C1	C2	C3	C4	C5	C6	C7
DMU13	0.2151	0.7473	0.0289	0.2627	0.2367	0.5384	0.9209
DMU14	0.0084	0.9915	0.0000	0.0098	0.0089	0.4883	0.0000
DMU15	0.0072	0.9909	0.0127	0.0083	0.0076	0.4394	0.4859
DMU16	0.0000	1.0000	0.0095	0.0000	0.0000	0.7270	0.4068
DMU17	0.0486	0.9515	0.0219	0.0541	0.0474	0.5171	0.7740
DMU18	0.4826	0.4552	0.0364	0.6741	0.5840	0.6249	0.9266
DMU19	0.2853	0.7131	0.0707	0.3233	0.3012	0.5043	0.8588
DMU20	0.0756	0.8961	0.0374	0.0898	0.0809	0.0000	0.7910
DMU21	0.0246	0.9763	0.0019	0.0225	0.0224	0.7621	0.6667
DMU22	0.0171	0.9839	0.0161	0.0167	0.0162	0.6136	0.2203
DMU23	0.0153	0.9837	0.0046	0.0171	0.0145	0.5144	0.8870
DMU24	0.0887	0.8990	0.0489	0.0985	0.0947	0.6464	0.9209
DMU25	0.0179	0.9813	0.0100	0.0184	0.0165	0.6893	0.2881
DMU26	0.0514	0.9300	0.3016	0.0589	0.0631	0.7747	0.7853

Table A10
Weighted input-output distance matrix (FY 2020-21)

Criteria DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.7722	0.8037	0.7364	0.7770	0.7713	0.7768	0.8128
DMU2	0.7593	0.8078	0.7713	0.7574	0.7574	0.7788	0.8157
DMU3	0.7213	0.8116	0.7925	0.7199	0.7189	0.7539	0.8048
DMU4	0.7736	0.8035	0.7505	0.7743	0.7714	0.7681	0.8203
DMU5	0.7403	0.8101	0.7891	0.7328	0.7375	0.7689	0.8159
DMU6	0.7547	0.8083	0.7391	0.7573	0.7529	0.7770	0.8180
DMU7	0.7309	0.8107	0.8212	0.7268	0.7287	0.7553	0.8347
DMU8	0.7034	0.8120	0.7777	0.7041	0.7016	0.7797	0.8223
DMU9	0.7763	0.8023	0.7578	0.7757	0.7739	0.7812	0.8345
DMU10	0.8132	0.0000	0.7319	0.8153	0.8133	0.7677	0.7853
DMU11	0.7263	0.8111	0.8053	0.7219	0.7264	0.7726	0.8214
DMU12	0.7708	0.8043	0.7918	0.7717	0.7691	0.7754	0.8270
DMU13	0.7629	0.8050	0.7203	0.7752	0.7668	0.7967	0.7700
DMU14	0.6783	0.8125	0.5860	0.6884	0.6781	0.7875	0.8114
DMU15	0.6628	0.8126	0.6980	0.6761	0.6674	0.7911	0.8022
DMU16	0.0000	0.8128	0.6907	0.0000	0.0000	0.7710	0.8280
DMU17	0.7211	0.8114	0.7065	0.7272	0.7197	0.7865	0.7754
DMU18	0.7820	0.7981	0.7170	0.7912	0.7838	0.7790	0.0000
DMU19	0.7711	0.8037	0.7452	0.7794	0.7732	0.8006	0.7772
DMU20	0.7328	0.8096	0.7275	0.7411	0.7370	0.8118	0.7461
DMU21	0.7070	0.8120	0.0000	0.7068	0.7042	0.7635	0.8111
DMU22	0.6959	0.8122	0.6981	0.6992	0.6937	0.7805	0.8139
DMU23	0.6902	0.8123	0.6718	0.6980	0.6893	0.7921	0.8163
DMU24	0.7354	0.8100	0.7351	0.7425	0.7386	0.7935	0.7761
DMU25	0.6987	0.8121	0.6834	0.7025	0.6967	0.7755	0.8277
DMU26	0.7194	0.8103	0.7842	0.7339	0.7286	0.0000	0.8353

Table A11
Weighted input-output distance matrix (FY 2021-22)

Criteria DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.0303	0.0881	0.0082	0.0363	0.0303	0.1341	0.1437
DMU2	0.0180	0.0989	0.0344	0.0196	0.0173	0.1094	0.1148
DMU3	0.0056	0.1103	0.0569	0.0058	0.0052	0.1492	0.1787
DMU4	0.0314	0.0871	0.0149	0.0333	0.0291	0.1135	0.1003
DMU5	0.0097	0.1056	0.0736	0.0077	0.0089	0.1163	0.1181
DMU6	0.0170	0.1004	0.0100	0.0181	0.0158	0.1129	0.1003
DMU7	0.0073	0.1078	0.1609	0.0066	0.0068	0.1148	0.0387
DMU8	0.0026	0.1121	0.0573	0.0026	0.0026	0.0568	0.0961
DMU9	0.0332	0.0857	0.0182	0.0342	0.0312	0.0987	0.0000
DMU10	0.1183	0.0000	0.0070	0.1285	0.1194	0.1343	0.1764
DMU11	0.0062	0.1089	0.1016	0.0054	0.0061	0.1250	0.0980
DMU12	0.0299	0.0893	0.0578	0.0309	0.0282	0.1174	0.0523
DMU13	0.0237	0.0881	0.0046	0.0347	0.0278	0.0985	0.1927
DMU14	0.0010	0.1135	0.0000	0.0016	0.0011	0.0835	0.0863
DMU15	0.0007	0.1137	0.0020	0.0010	0.0007	0.0224	0.1321
DMU16	0.0000	0.1147	0.0015	0.0000	0.0000	0.0886	0.0910
DMU17	0.0050	0.1096	0.0030	0.0065	0.0050	0.0870	0.1792
DMU18	0.0453	0.0718	0.0041	0.0640	0.0492	0.1281	0.2091
DMU19	0.0308	0.0844	0.0112	0.0413	0.0336	0.0934	0.1862
DMU20	0.0082	0.1033	0.0060	0.0108	0.0093	0.0000	0.1941
DMU21	0.0030	0.1114	0.0002	0.0029	0.0028	0.1312	0.1078
DMU22	0.0020	0.1126	0.0020	0.0023	0.0019	0.0726	0.1111
DMU23	0.0016	0.1129	0.0007	0.0022	0.0016	0.0657	0.1162
DMU24	0.0088	0.1044	0.0079	0.0123	0.0100	0.1127	0.1941
DMU25	0.0022	0.1122	0.0012	0.0024	0.0021	0.0740	0.0854
DMU26	0.0054	0.1065	0.0422	0.0081	0.0073	0.1137	0.0126

Table A12
Weighted input-output distance matrix (FY 2022-23)

Criteria DMU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.0327	0.0901	0.0083	0.0377	0.0318	0.1079	0.1550
DMU2	0.0180	0.1034	0.0347	0.0194	0.0177	0.1032	0.0898
DMU3	0.0061	0.1157	0.0573	0.0066	0.0056	0.1370	0.2093
DMU4	0.0321	0.0895	0.0150	0.0338	0.0294	0.0824	0.0839
DMU5	0.0095	0.1108	0.0740	0.0079	0.0086	0.1085	0.1542
DMU6	0.0167	0.1055	0.0101	0.0179	0.0154	0.0998	0.0754
DMU7	0.0068	0.1131	0.1620	0.0069	0.0066	0.0947	0.0805
DMU8	0.0026	0.1175	0.0577	0.0027	0.0027	0.0567	0.0746
DMU9	0.0349	0.0891	0.0183	0.0341	0.0319	0.1014	0.0000
DMU10	0.1213	0.0000	0.0070	0.1287	0.1216	0.1116	0.1737
DMU11	0.0065	0.1138	0.1022	0.0059	0.0063	0.1031	0.1211
DMU12	0.0304	0.0915	0.0582	0.0307	0.0280	0.0912	0.0864
DMU13	0.0257	0.0906	0.0047	0.0348	0.0287	0.0887	0.1957
DMU14	0.0011	0.1189	0.0000	0.0014	0.0011	0.0517	0.0305
DMU15	0.0008	0.1191	0.0020	0.0010	0.0008	0.0163	0.1423
DMU16	0.0000	0.1202	0.0015	0.0000	0.0000	0.0834	0.1322
DMU17	0.0055	0.1147	0.0030	0.0067	0.0054	0.0748	0.1720
DMU18	0.0514	0.0680	0.0042	0.0644	0.0541	0.1019	0.2076

Table A12
Weighted input-output distance matrix (FY 2022-23)

Criteria DMU	C1	C2	C3	C4	C5	C6	C7
DMU19	0.0321	0.0854	0.0114	0.0417	0.0347	0.0817	0.1872
DMU20	0.0089	0.1076	0.0060	0.0113	0.0098	0.0000	0.1804
DMU21	0.0030	0.1170	0.0003	0.0029	0.0029	0.1197	0.0932
DMU22	0.0020	0.1181	0.0021	0.0021	0.0019	0.0583	0.0864
DMU23	0.0017	0.1184	0.0007	0.0022	0.0017	0.0683	0.1677
DMU24	0.0096	0.1079	0.0079	0.0125	0.0105	0.0925	0.1991
DMU25	0.0022	0.1178	0.0012	0.0024	0.0020	0.0827	0.0729
DMU26	0.0056	0.1113	0.0488	0.0078	0.0075	0.0576	0.1601

Table A13
Weighted input-output distance matrix (FY 2023-24)

Criteria MU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.0338	0.0975	0.0084	0.0414	0.0338	0.0711	0.1474
DMU2	0.0185	0.1116	0.0392	0.0217	0.0193	0.0722	0.0857
DMU3	0.0066	0.1238	0.0613	0.0075	0.0063	0.1012	0.2023
DMU4	0.0332	0.0970	0.0152	0.0366	0.0318	0.0673	0.0800
DMU5	0.0095	0.1193	0.0753	0.0093	0.0093	0.0868	0.1760
DMU6	0.0173	0.1134	0.0111	0.0198	0.0168	0.0729	0.1600
DMU7	0.0070	0.1209	0.1648	0.0081	0.0072	0.0820	0.0846
DMU8	0.0027	0.1255	0.0587	0.0029	0.0028	0.0462	0.0389
DMU9	0.0347	0.0967	0.0186	0.0364	0.0333	0.0760	0.1417
DMU10	0.1255	0.0000	0.0072	0.1447	0.1331	0.0826	0.1600
DMU11	0.0064	0.1219	0.1040	0.0067	0.0066	0.0812	0.1234
DMU12	0.0309	0.1004	0.0662	0.0338	0.0297	0.0689	0.1074
DMU13	0.0270	0.0960	0.0048	0.0380	0.0315	0.0545	0.1863
DMU14	0.0011	0.1274	0.0000	0.0014	0.0012	0.0494	0.0000
DMU15	0.0009	0.1273	0.0021	0.0012	0.0010	0.0445	0.0983
DMU16	0.0000	0.1284	0.0016	0.0000	0.0000	0.0735	0.0823
DMU17	0.0061	0.1222	0.0036	0.0078	0.0063	0.0523	0.1566
DMU18	0.0606	0.0585	0.0060	0.0976	0.0777	0.0632	0.1874
DMU19	0.0358	0.0916	0.0116	0.0468	0.0401	0.0510	0.1737
DMU20	0.0095	0.1151	0.0062	0.0130	0.0108	0.0000	0.1600
DMU21	0.0031	0.1254	0.0003	0.0033	0.0030	0.0771	0.1349
DMU22	0.0021	0.1264	0.0027	0.0024	0.0022	0.0621	0.0446
DMU23	0.0019	0.1264	0.0008	0.0025	0.0019	0.0520	0.1794
DMU24	0.0111	0.1155	0.0081	0.0143	0.0126	0.0654	0.1863
DMU25	0.0022	0.1260	0.0016	0.0027	0.0022	0.0697	0.0583
DMU26	0.0065	0.1195	0.0497	0.0085	0.0084	0.0784	0.1589

Table A14
Weighted input-output distance matrix (FY 2024-25)

Criteria MU	C1	C2	C3	C4	C5	C6	C7
DMU1	0.7738	0.8055	0.7330	0.7784	0.7745	0.7653	0.8010
DMU2	0.7562	0.8096	0.7777	0.7596	0.7585	0.7707	0.8156
DMU3	0.7274	0.8132	0.7938	0.7297	0.7279	0.0000	0.0000
DMU4	0.7735	0.8053	0.7499	0.7743	0.7728	0.7772	0.8091
DMU5	0.7361	0.8121	0.7988	0.7352	0.7356	0.7482	0.6950
DMU6	0.7532	0.8105	0.7410	0.7556	0.7533	0.7666	0.7784

Table A14
Weighted input-output distance matrix (FY 2024-25)

Criteria	MU	C1	C2	C3	C4	C5	C6	C7
DMU7	0.7278	0.8127	0.8225	0.7310	0.7299	0.7656	0.7986
DMU8	0.7015	0.8139	0.7913	0.7031	0.7033	0.7813	0.8218
DMU9	0.7757	0.8049	0.7571	0.7749	0.7751	0.7645	0.7828
DMU10	0.8136	0.0000	0.7285	0.8164	0.8152	0.7640	0.7911
DMU11	0.7260	0.8128	0.8090	0.7268	0.7273	0.7579	0.7941
DMU12	0.7703	0.8066	0.7935	0.7710	0.7694	0.7756	0.8046
DMU13	0.7670	0.8050	0.7172	0.7740	0.7715	0.7844	0.7751
DMU14	0.6784	0.8143	0.0000	0.6835	0.6799	0.7886	0.8319
DMU15	0.6764	0.8142	0.6950	0.6821	0.6796	0.7940	0.8278
DMU16	0.0000	0.8146	0.7027	0.0000	0.0000	0.7722	0.8230
DMU17	0.7250	0.8128	0.7099	0.7296	0.7262	0.7886	0.7878
DMU18	0.7924	0.7875	0.7238	0.8021	0.7985	0.7861	0.7866
DMU19	0.7765	0.8031	0.7427	0.7818	0.7798	0.7838	0.7854
DMU20	0.7360	0.8108	0.7243	0.7409	0.7399	0.8075	0.8214
DMU21	0.7057	0.8138	0.6460	0.7051	0.7047	0.7619	0.8141
DMU22	0.6949	0.8140	0.7013	0.6959	0.6944	0.7852	0.8336
DMU23	0.6941	0.8125	0.6683	0.6983	0.6940	0.7882	0.7138
DMU24	0.7417	0.8109	0.7318	0.7470	0.7465	0.7747	0.7671
DMU25	0.6957	0.8140	0.6884	0.6991	0.6953	0.7793	0.8202
DMU26	0.7251	0.8122	0.7875	0.7310	0.7319	0.7807	0.7647

Table A15
Calculation of efficiency scores and ranking of DMUs in FY 2020-21

DMU	Ei	AS	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU1	0.0463	0.6006	0.3355	0.0463	0.1909	8	18	9
DMU2	0.0458	0.6226	0.3310	0.0458	0.1884	13	22	17
DMU3	0.0504	0.5778	0.3421	0.0504	0.1962	4	8	4
DMU4	0.0464	0.6052	0.3347	0.0464	0.1905	11	17	11
DMU5	0.0471	0.6126	0.3336	0.0471	0.1904	12	15	14
DMU6	0.0459	0.6493	0.3261	0.0459	0.1860	17	21	18
DMU7	0.0465	0.5754	0.3406	0.0465	0.1936	5	16	5
DMU8	0.0458	0.6758	0.3212	0.0458	0.1835	20	23	21
DMU9	0.0433	0.6650	0.3219	0.0433	0.1826	18	26	24
DMU10	0.0547	0.3407	0.4003	0.0547	0.2275	2	4	3
DMU11	0.0462	0.6039	0.3348	0.0462	0.1905	9	19	12
DMU12	0.0446	0.6005	0.3347	0.0446	0.1897	10	25	15
DMU13	0.0491	0.6069	0.3357	0.0491	0.1924	7	10	6
DMU14	0.0475	0.7003	0.3178	0.0475	0.1827	24	13	23
DMU15	0.0478	0.6907	0.3196	0.0478	0.1837	23	11	20
DMU16	0.0617	0.7209	0.3214	0.0617	0.1915	19	3	8
DMU17	0.0504	0.6388	0.3303	0.0504	0.1904	14	7	13
DMU18	0.1376	0.4983	0.4025	0.1376	0.2701	1	1	1
DMU19	0.0476	0.5993	0.3364	0.0476	0.1920	6	12	7
DMU20	0.0505	0.6972	0.3199	0.0505	0.1852	21	6	19
DMU21	0.0536	0.6602	0.3280	0.0536	0.1908	16	5	10
DMU22	0.0472	0.6888	0.3197	0.0472	0.1834	22	14	22
DMU23	0.0457	0.7206	0.3135	0.0457	0.1796	26	24	26
DMU24	0.0491	0.6412	0.3292	0.0491	0.1892	15	9	16
DMU25	0.0462	0.7212	0.3136	0.0462	0.1799	25	20	25
DMU26	0.1327	0.6587	0.3678	0.1327	0.2502	3	2	2

Table A16
Calculation of efficiency scores and ranking of DMUs in FY 2021-22

DMU	Ei	AS	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU1	0.0514	0.5432	0.3497	0.0514	0.2005	4	7	4
DMU2	0.0469	0.5987	0.3362	0.0469	0.1915	13	16	14
DMU3	0.1401	0.5277	0.3974	0.1401	0.2688	3	1	2
DMU4	0.0467	0.5913	0.3375	0.0467	0.1921	12	17	11
DMU5	0.0479	0.5803	0.3403	0.0479	0.1941	10	14	10
DMU6	0.0469	0.6298	0.3303	0.0469	0.1886	15	15	17
DMU7	0.0455	0.5622	0.3428	0.0455	0.1941	8	21	9
DMU8	0.0441	0.6802	0.3196	0.0441	0.1818	19	25	22
DMU9	0.0431	0.6671	0.3215	0.0431	0.1823	18	26	20
DMU10	0.0583	0.3161	0.4090	0.0583	0.2337	2	4	3
DMU11	0.0483	0.5668	0.3433	0.0483	0.1958	7	13	8
DMU12	0.0456	0.5851	0.3382	0.0456	0.1919	11	20	13
DMU13	0.0521	0.5596	0.3467	0.0521	0.1994	6	6	6
DMU14	0.0499	0.7153	0.3164	0.0499	0.1831	22	11	19
DMU15	0.0453	0.7421	0.3097	0.0453	0.1775	26	22	26
DMU16	0.0608	0.7088	0.3230	0.0608	0.1919	17	3	12
DMU17	0.0503	0.6359	0.3308	0.0503	0.1905	14	10	15
DMU18	0.1397	0.4566	0.4131	0.1397	0.2764	1	2	1
DMU19	0.0504	0.5450	0.3488	0.0504	0.1996	5	9	5
DMU20	0.0491	0.7001	0.3187	0.0491	0.1839	21	12	18
DMU21	0.0510	0.6516	0.3282	0.0510	0.1896	16	8	16
DMU22	0.0459	0.7052	0.3161	0.0459	0.1810	23	19	23
DMU23	0.0459	0.7101	0.3154	0.0459	0.1806	24	18	24
DMU24	0.0540	0.5862	0.3422	0.0540	0.1981	9	5	7
DMU25	0.0451	0.7221	0.3129	0.0451	0.1790	25	23	25
DMU26	0.0450	0.6882	0.3187	0.0450	0.1819	20	24	21

Table A17
Calculation of efficiency scores and ranking of DMUs in FY 2022-23

DMU	Ei	AS	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU1	0.0498	0.5494	0.3476	0.0498	0.1987	5	10	6
DMU2	0.0466	0.6140	0.3331	0.0466	0.1898	12	17	13
DMU3	0.2279	0.5053	0.4461	0.2279	0.3370	1	1	1
DMU4	0.0447	0.6275	0.3296	0.0447	0.1871	15	24	17
DMU5	0.0501	0.5544	0.3467	0.0501	0.1984	7	9	7
DMU6	0.0461	0.6526	0.3256	0.0461	0.1859	18	18	19
DMU7	0.0458	0.5454	0.3464	0.0458	0.1961	8	21	10
DMU8	0.0439	0.6902	0.3178	0.0439	0.1809	21	26	22
DMU9	0.0443	0.6558	0.3241	0.0443	0.1842	20	25	20
DMU10	0.0561	0.3303	0.4039	0.0561	0.2300	2	4	2
DMU11	0.0480	0.5627	0.3439	0.0480	0.1960	9	13	11
DMU12	0.0452	0.5831	0.3384	0.0452	0.1918	11	22	12
DMU13	0.0529	0.5595	0.3471	0.0529	0.2000	6	6	4
DMU14	0.0473	0.7798	0.3046	0.0473	0.1760	26	14	26
DMU15	0.0459	0.7396	0.3104	0.0459	0.1782	25	19	24
DMU16	0.0634	0.6786	0.3296	0.0634	0.1965	14	2	9
DMU17	0.0495	0.6453	0.3286	0.0495	0.1890	16	12	14
DMU18	0.0602	0.4719	0.3698	0.0602	0.2150	3	3	3
DMU19	0.0506	0.5505	0.3478	0.0506	0.1992	4	7	5
DMU20	0.0472	0.7091	0.3161	0.0472	0.1817	22	15	21

Table A17
Continued

DMU	Ei	AS	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU21	0.0505	0.6621	0.3261	0.0505	0.1883	17	8	16
DMU22	0.0449	0.7311	0.3113	0.0449	0.1781	24	23	25
DMU23	0.0495	0.6665	0.3248	0.0495	0.1871	19	11	18
DMU24	0.0545	0.5949	0.3407	0.0545	0.1976	10	5	8
DMU25	0.0459	0.7153	0.3144	0.0459	0.1802	23	20	23
DMU26	0.0471	0.6312	0.3301	0.0471	0.1886	13	16	15

Table A18
Calculation of efficiency scores and ranking of DMUs in FY 2023-24

DMU	Ei	AS	IE	CE	OE	Rank (IE)	Rank (CE)	Rank (OE)
DMU1	0.0496	0.5642	0.3445	0.0496	0.1970	10	15	11
DMU2	0.0471	0.6161	0.3330	0.0471	0.1900	15	21	18
DMU3	0.2275	0.5019	0.4467	0.2275	0.3371	1	1	1
DMU4	0.0464	0.6194	0.3319	0.0464	0.1891	16	25	19
DMU5	0.0548	0.5253	0.3552	0.0548	0.2050	4	4	4
DMU6	0.0510	0.5912	0.3397	0.0510	0.1954	13	11	15
DMU7	0.0487	0.5235	0.3525	0.0487	0.2006	5	18	5
DMU8	0.0445	0.7079	0.3150	0.0445	0.1798	22	26	24
DMU9	0.0498	0.5576	0.3459	0.0498	0.1978	7	14	7
DMU10	0.0565	0.3356	0.4026	0.0565	0.2296	2	3	2
DMU11	0.0501	0.5516	0.3473	0.0501	0.1987	6	12	6
DMU12	0.0472	0.5574	0.3447	0.0472	0.1959	9	20	13
DMU13	0.0524	0.5786	0.3429	0.0524	0.1977	12	8	8
DMU14	0.0487	0.7847	0.3045	0.0487	0.1766	26	17	26
DMU15	0.0470	0.7212	0.3140	0.0470	0.1805	24	22	23
DMU16	0.0643	0.6938	0.3274	0.0643	0.1958	19	2	14
DMU17	0.0495	0.6551	0.3269	0.0495	0.1882	20	16	20
DMU18	0.0529	0.4595	0.3691	0.0529	0.2110	3	6	3
DMU19	0.0500	0.5633	0.3448	0.0500	0.1974	8	13	10
DMU20	0.0469	0.7185	0.3144	0.0469	0.1807	23	23	22
DMU21	0.0513	0.6462	0.3294	0.0513	0.1903	17	10	17
DMU22	0.0464	0.7309	0.3121	0.0464	0.1792	25	24	25
DMU23	0.0527	0.6519	0.3290	0.0527	0.1908	18	7	16
DMU24	0.0537	0.6004	0.3393	0.0537	0.1965	14	5	12
DMU25	0.0475	0.7112	0.3160	0.0475	0.1817	21	19	21
DMU26	0.0518	0.5764	0.3431	0.0518	0.1974	11	9	9

Conflict of Interest

The authors declare no conflict of interest.

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