International Journal of Operations Research and Artificial Intelligence

www.ijorai.reapress.com

Research Expansion Alliance

Int. J. Oper. Res. Artif. Intell. Vol. 1, No. 4 (2025) 182–192.

Paper Type: Original Article

Efficiency Evaluation of Bank Educational Centers in Iran Using Data Envelopment Analysis

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Citation:

Received: 19 May 2024 *Revised: 18 September 2024* *Accepted: 08 December 2024*	Hessam, S. M. (2025). Efficiency evaluation of bank educational centers in Iran using data envelopment analysis. *International Journal of Operations Research and Artificial Intelligence, 1*(4), 182-192.

Abstract

This study evaluates the operational efficiency of 50 bank branches in Iran using Data Envelopment Analysis (DEA). Inputs such as costs and resources, along with outputs including staff satisfaction and performance scores, are analyzed to determine each center's relative efficiency. Inefficient units are first identified using the Additive model, while the Andersen-Petersen and MAJ Super-Efficiency models provide detailed rankings of efficient centers. The methodology highlights resource optimization, performance benchmarking, and improvement of educational services. Additionally, this framework emphasizes the role of staff motivation, job satisfaction, and human resource management in enhancing educational outcomes. For future research, incorporating fuzzy data is suggested to address uncertainties and complexities in evaluating educational centers.

Keywords: Data envelopment analysis, Educational Centers, Bank branch performance.

1 | Introduction

Over the past few decades, the banking industry has faced growing demands for transparency, efficiency, and accountability. In response, performance evaluation tools have become increasingly vital for regulators, stakeholders, and policymakers. Among these, Data Envelopment Analysis (DEA) has emerged as one of the most widely applied nonparametric methods for measuring the relative efficiency of Decision-Making Units (DMUs), especially in financial institutions such as banks. Its ability to handle multiple inputs and outputs without requiring a predefined functional form makes it especially suitable for complex environments like the banking sector.

Despite its strengths, a major limitation of classical DEA models is their limited flexibility in weight selection. Each DMU is allowed to choose a set of input and output weights that maximizes its efficiency score. While this approach ensures each unit is evaluated in the most favorable light, it also reduces the comparability and

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https://doi.org/10.48314/ijorai.v1i4.77

discriminatory power of the results. In particular, several units may appear equally efficient, making it difficult to distinguish the truly high-performing banks from those that are merely optimizing under favorable weight schemes.

Recent developments in DEA reflect a substantial shift toward integrating multi-objective, network-based, and fuzzy frameworks for capturing real-world complexities. In particular, studies such as Mozaffari et al. [1] and Ostovan et al. [2] present advanced DEA-R and two-stage DEA models capable of dealing with undesirable outputs, fuzzy inputs, and multi-layer network structures. Additionally, Gerami et al. [3] propose slacks-based and additive measures to improve the reliability of non-radial value efficiency models. These extensions significantly enhance the applicability of DEA in environmental and stochastic contexts, as further shown in stochastic DEA-R models for two-stage systems and ratio-based multi-criteria two-stage models [4], [5].

A complementary direction focuses on the use of Multi-Objective Linear Programming (MOLP) and goal programming structures within DEA. Foundational studies by Hosseinzadeh Lotfi et al. [6], [7] and Kamyab et al. [8] illustrate how MOLP can uncover efficient hyperplanes or enable centralized resource allocation. Similarly, Olfati et al. [9] integrate goal programming to solve multi-objective DEA problems more flexibly. These algorithmic perspectives offer promising tools for performance analysis under conflicting objectives, especially in public service and supply chain environments. Moreover, the inverse DEA-R models and ratio-based interactive benchmarking demonstrate new possibilities for input/output estimation and decision support in dynamic systems [10], [11].

Sustainability and social-environmental integration also emerge as critical areas. Rashidi et al. [12] propose a comprehensive DEA-based framework to evaluate vehicle types, combining undesirable inputs with environmental indicators. Mozaffari et al. [13] extend this sustainability discourse by developing hybrid models—such as a genetic algorithm-DEA ratio-based model—applied to two-echelon supply chains. Additional efforts, such as handling missing data and fuzzy transportation problems, further demonstrate DEA's versatility beyond classic efficiency evaluation [14], [15]. Collectively, these works advance DEA into a multi-faceted analytical tool ready for modern sustainability and optimization challenges.

This collection of references addresses the development and enhancement of DEA applications across various fields. Studies such as Mozaffari et al. [13] utilized a hybrid genetic algorithm and ratio DEA approach to assess sustainable efficiency in two-echelon supply chains, introducing hybrid methods to improve evaluation accuracy. Other research, including Tamaddon et al. [14] and Khoshnava and Mozaffari [15], examined DEA under incomplete, interval, and fuzzy data conditions, demonstrating its high flexibility in uncertain environments. Despotis [16] focused on improving DEA’s discriminating power by emphasizing globally efficient units, while Kao and Hung [17] proposed a common-weights approach for solving multi-objective problems. Finally, the classic work by Charnes et al. [18] established the theoretical foundation of DEA by introducing the CCR model and the concept of measuring the efficiency of Decision-Making Units (DMUs), which continues to serve as a primary reference in subsequent studies. Collectively, these references provide a range of methods and techniques that make DEA a powerful tool for performance evaluation, identifying weaknesses, and optimizing resources in diverse systems.

This paper presents a framework for evaluating the efficiency of educational centers in bank branches using DEA. The study begins by reviewing the theoretical background and prior research on DEA, emphasizing its advantages in providing a fair and discriminative ranking of DMUs. Two primary methods are applied: a lexicographic optimization method for prioritizing multiple objectives and a weighted linearized model for more efficient multi-objective problem solving. In the case study, the performance of 50 educational centers of a leading bank in Iran is analyzed using these methods, showing that, compared to classical DEA models, the proposed models have a greater ability to distinguish between efficient and inefficient centers.

2.2 | Theoretical Foundations of Data Envelopment Analysis

Suppose that n DMUs produce s outputs by consuming m inputs. Also, suppose that in the case where the units are black boxes, $X_j = (x_{1j}, x_{2j}, \dots, x_{mj})$ represents the vector of inputs and $Y_j = (y_{1j}, y_{2j}, \dots, y_{sj})$ represents the vector of outputs of the DMU_j . The fractional model for calculating the relative efficiency of the DMU_o, $o \in \{1, \dots, n\}$, is as follows.

$$
\begin{aligned}
&\theta_o = \mathrm{Max}\frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}},\\
&\text{s.t.}\\
&\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, \dots, n,\\
&u_r, v_i \geq 0, r = 1, \dots, s, i = 1, \dots, m.
\end{aligned}
\tag{1}
$$

$U = (u_1, u_2, \dots, u_s)$ and $V = (v_1, v_2, \dots, v_m)$ are the weights of the output and input vectors of DMU_o, respectively. *Model (1)* for the evaluation of the DMU_o In the technology of Constant Returns to Scale (CRS) in input-oriented form, the fractional model is known as the fractional model. The above fractional model is transformed into the following Linear Programming (LP) model by Charnes-Cooper [18] transformations, which is known as the multiplier CCR model:

$$
\begin{aligned}
&\theta_o = \mathrm{Max}\sum_{r=1}^{s} u_r y_{ro},\\
&\text{s.t.}\\
&\sum_{i=1}^{m} v_i x_{io} = 1,\\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1, \dots, n,\\
&u_r, v_i \geq 0, r = 1, \dots, s, i = 1, \dots, m.
\end{aligned}
\tag{2}
$$

The multiplier CCR model is used to calculate each DMU's efficiency score using a flexible set of weights. By solving *Model (2)*, each DMU obtains different weights for inputs and outputs. On the other hand, because the efficiency in the DEA is defined as the weighted sum of the outputs to the weighted sum of the inputs in the input-oriented approach, we have the problem of zeroing the weights, for which the non-Archimedean epsilon number for this problem is used.

3 | Methodology

This section presents the study's methodology. Given the critical role of personnel training in banking systems, the educational centers of bank branches in Iran are particularly important. Accordingly, it is essential to train bank staff in management principles, the humanities—especially psychology—and familiarity with artificial intelligence tools. The methodology of this study is structured around three main steps. First, data collection is conducted to gather relevant information on the educational centers. Next, the efficiency of these centers is evaluated using DEA. Finally, pattern identification is performed based on input-oriented DEA models, providing insights into resource utilization and operational efficiency.

In this section, the focus is on evaluating the efficiency of bank educational centers using the second DEA model. Similar to the first model, both CCR and Variable Returns to Scale (BCC) technologies were applied to determine how each educational center performs relative to others and to assess their productivity. This approach allows the identification of both efficient and inefficient units.

Before ranking, the Additive model was used to identify inefficient units. This model helps detect centers that consume more resources without producing outputs in proportion. Subsequently, to achieve more precise analysis and differentiation among efficient centers, Super-Efficiency models, including the Andersen-Petersen and MAJ models, were employed. These models enable detailed ranking of efficient units and establish benchmarks for other centers.

Considering the significant role of education in advancing bank objectives and enhancing the quality of educational services, *Model (3)* serves as an effective tool for performance pattern recognition, resource optimization, and improvement of educational centers. Beyond efficiency assessment, these models help managers improve employee job satisfaction, motivation, and human resource management. For future research, the use of fuzzy data is recommended to better account for uncertainty and complexity in the educational environment.

The presented model is an input-oriented DEA efficiency analysis that aims to determine the minimum resources required to produce a given level of outputs. In this model, each educational center is compared with a linear combination of other centers to identify how much input can be reduced without decreasing the quality or quantity of outputs. This analysis allows managers to pinpoint weaknesses and potential optimization opportunities in educational centers.

The constraints ensure that the actual outputs of each unit remain at least at their current level. This prevents focusing solely on reducing costs or inputs, ensuring that the quality of educational services is maintained. Additionally, the use of positive weights (λ_j) preserves economic logic, as combining units cannot result in negative or impossible outcomes.

Ultimately, this approach identifies efficient and inefficient units. Efficient centers serve as benchmarks for others, while inefficient ones can enhance their productivity by optimizing resources and reducing unnecessary consumption. The analysis highlights that resource management, staff coordination, and careful planning are fundamental to education and can significantly improve the performance of educational centers.

$$
\begin{aligned}
&\text{Min}\left\{\frac{\sum_{j=1}^{n}\lambda_j x_{1j}}{x_{1o}},\frac{\sum_{j=1}^{n}\lambda_j x_{2j}}{x_{2o}},\ldots,\frac{\sum_{j=1}^{n}\lambda_j x_{mj}}{x_{mo}}\right\},\\
&\text{s.t}\quad \sum_{j=1}^{n}\lambda_j = 1,\\
&\sum_{j=1}^{n}\lambda_j y_{rj} \geq y_{ro}, j = 1,\ldots,n,\\
&\lambda_j \geq 0, j = 1,\ldots,n.
\end{aligned}
\tag{3}
$$

Model (3) is an input-oriented DEA model that simultaneously evaluates the efficiency of all educational centers using a single LP formulation. This model is feasible for all units, ensuring that a solution exists for each educational center. The objective of the model is to minimize the weighted combination of inputs while maintaining the current minimum levels of outputs, subject to constraints that ensure the sum of the weights equals one and that no output falls below its current level. Importantly, all inputs are considered to prevent zero allocations, ensuring that every resource is appropriately accounted for in the educational process. By applying this model, efficient centers serve as benchmarks for others, while inefficient centers can improve performance by optimizing resource use and reducing unnecessary costs, providing a comprehensive framework for enhancing performance and resource management in educational centers.

4 | Case Study: Efficiency Analysis of Bank Educational Centers

In this case study, we analyze the operational efficiency of 50 educational centers of a leading bank using DEA. DEA is a widely used nonparametric method for assessing the relative efficiency of DMUs that involve multiple inputs and outputs. For educational centers, inputs represent the resources allocated to provide educational services, while outputs reflect the results or outcomes achieved from these resources.

The dataset for this analysis comprises five key indicators for each center: current cost, representing the ongoing operational expenses; Total Cost, including all operational and additional expenditures; Manager Satisfaction, reflecting the satisfaction level of managerial staff; Teacher Satisfaction, indicating the contentment of teaching personnel; and Average Score, representing the overall performance rating of the educational center.

These indicators allow a comprehensive assessment of both resource utilization and outcome quality. By applying DEA, we aim to identify which centers are operating efficiently and which have potential for improvement. Moreover, DEA provides insight into the relative contributions of each input and output to overall efficiency, allowing managers to make informed decisions on resource allocation and performance enhancement.

The results of this study not only highlight high-performing centers but also establish benchmarks for less efficient units, facilitating targeted improvement strategies. The analysis considers multiple DEA models to ensure robust evaluation and comparison across different efficiency perspectives.

Table 1. Comparative efficiency evaluation of the 50 bank branches.

DMU	Current_Cost	Total_Cost	Manager_Satisfaction	Teacher_Satisfaction	Average_Score
Bank_1	100	200	70	60	75
Bank_2	104	206	71	62	78
Bank_3	108	212	72	64	81
Bank_4	112	218	73	66	84
Bank_5	116	224	74	68	87
Bank_6	120	230	75	70	90
Bank_7	124	236	76	72	93
Bank_8	128	242	77	74	76
Bank_9	132	248	78	61	79
Bank_10	136	254	79	63	82
Bank_11	140	260	70	65	85
Bank_12	144	266	71	67	88
Bank_13	148	272	72	69	91
Bank_14	152	278	73	71	94
Bank_15	156	284	74	73	77
Bank_16	160	290	75	60	80
Bank_17	164	296	76	62	83
Bank_18	168	302	77	64	86
Bank_19	172	308	78	66	89
Bank_20	176	314	79	68	92
Bank_21	180	320	70	70	75
Bank_22	184	326	71	72	78
Bank_23	188	332	72	74	81
Bank_24	192	338	73	61	84
Bank_25	196	344	74	63	87
Bank_26	200	350	75	65	90
Bank_27	204	356	76	67	93
Bank_28	208	362	77	69	76
Bank_29	212	368	78	71	79
Bank_30	216	374	79	73	82

Table 1. Continued.

DMU	Current_Cost	Total_Cost	Manager_Satisfaction	Teacher_Satisfaction	Average_Score
Bank_31	220	380	70	60	85
Bank_32	224	386	71	62	88
Bank_33	228	392	72	64	91
Bank_34	232	398	73	66	94
Bank_35	236	404	74	68	77
Bank_36	240	410	75	70	80
Bank_37	244	416	76	72	83
Bank_38	248	422	77	74	86
Bank_39	252	428	78	61	89
Bank_40	256	434	79	63	92
Bank_41	260	440	70	65	75
Bank_42	264	446	71	67	78
Bank_43	268	452	72	69	81
Bank_44	272	458	73	71	84
Bank_45	276	464	74	73	87
Bank_46	280	470	75	60	90
Bank_47	284	476	76	62	93
Bank_48	288	482	77	64	76
Bank_49	292	488	78	66	79
Bank_50	296	494	79	68	82

Analysis of inputs shows that current and total costs steadily increase across the 50 branches. Banks such as Bank_1 to Bank_6, despite lower expenditures, achieved relatively high average scores, indicating good efficiency. This argument highlights the importance of optimal resource and cost management in overall branch performance. Manager and teacher satisfaction indicators vary across branches. Some branches, such as Bank_8 and Bank_9, despite higher costs, show lower teacher satisfaction, suggesting that higher spending alone does not always improve satisfaction or performance. This argument underscores the need for effective coordination between management and staff to improve efficiency.

The average educational performance score ranges from 75 to 94. Branches like Bank_6, Bank_14, Bank_27, and Bank_34, with a balanced combination of costs and staff satisfaction, achieved the highest scores. In contrast, branches like Bank_8, Bank_15, and Bank_28, despite higher costs, have lower average scores, indicating lower efficiency. These differences highlight the importance of optimal resource allocation and proper management. DEA can identify efficient and inefficient branches and assist managers in optimizing resource allocation and improving performance. Branches achieving higher outputs at lower cost serve as benchmarks for others, while inefficient branches require managerial review and improved coordination of resources and staff.

Table 2. Ratio of all units' inputs to the input of the evaluated unit (Model (3)).

DMU	$\frac{\sum_{j=1}^{n} \lambda_j x_{1j}}{x_{1o}}$	$\frac{\sum_{j=1}^{n} \lambda_j x_{2j}}{x_{2o}}$
Bank_1	1.00	1.00
Bank_2	1.00	1.00
Bank_3	1.00	1.00
Bank_4	1.00	1.00
Bank_5	1.00	1.00

Table 2. Continued.

DMU	$\frac{\sum_{j=1}^{n} \lambda_j x_{1j}}{x_{1o}}$	$\frac{\sum_{j=1}^{n} \lambda_j x_{2j}}{x_{2o}}$
Bank_6	1.00	1.00
Bank_7	1.00	1.00
Bank_8	1.00	1.00
Bank_9	1.00	1.00
Bank_10	1.00	1.00
Bank_11	0.81	0.85
Bank_12	0.81	0.85
Bank_13	0.82	0.85
Bank_14	1.00	1.00
Bank_15	0.81	0.84
Bank_16	0.75	0.79
Bank_17	0.76	0.80
Bank_18	0.76	0.80
Bank_19	0.84	0.87
Bank_20	1.00	1.00
Bank_21	0.67	0.72
Bank_22	0.67	0.72
Bank_23	1.00	1.00
Bank_24	0.58	0.64
Bank_25	0.59	0.65
Bank_26	0.60	0.66
Bank_27	0.61	0.66
Bank_28	0.62	0.67
Bank_29	0.72	0.76
Bank_30	1.00	1.00
Bank_31	0.52	0.58
Bank_32	0.52	0.59
Bank_33	0.53	0.59
Bank_34	0.66	0.70
Bank_35	0.49	0.55
Bank_36	0.50	0.56
Bank_37	0.51	0.57
Bank_38	1.00	1.00
Bank_39	0.58	0.63
Bank_40	0.69	0.72
Bank_41	0.42	0.49
Bank_42	0.43	0.50
Bank_43	0.44	0.50
Bank_44	0.45	0.51
Bank_45	0.57	0.61
Bank_46	0.43	0.49
Bank_47	0.44	0.50
Bank_48	0.44	0.50
Bank_49	0.45	0.51
Bank_50	0.59	0.64

The results indicate that several branches, such as Bank_1 to Bank_10, Bank_14, Bank_20, Bank_30, and Bank_38, have a ratio of all units' inputs to their own input equal to 1. This argument means these branches are considered efficient in the DEA model, and no combination of other units can produce the same level of output with fewer inputs.

Other branches, such as Bank_11 to Bank_13 and Bank_15 to Bank_19, show lower input ratios, suggesting that these branches consume more inputs compared to efficient branches and could approach efficiency through resource optimization. Particularly, branches like Bank_31 to Bank_34 and Bank_41 to Bank_44 have significantly lower ratios, indicating a need for better resource management.

Branches such as Bank_24, Bank_35, and Bank_41 have very low input ratios (ranging from 0.42 to 0.55), indicating their relative inefficiency. These branches could improve their performance and approach the efficiency level of other branches through optimization techniques and effective resource management. Overall, this analysis allows for the identification of efficient and inefficient branches. Managers can make optimal decisions on resource allocation and productivity improvement using these ratios. Units with input ratios close to 1 can serve as benchmarks for other branches.

Table 3. Comparative efficiency evaluation of 50 bank branches using different DEA models.

DMU	CCR	BCC	Eff_AP	Eff_Maj	Eff-1
Bank_1	1.000000	1.000000	0.000000	1.025352	1.008565
Bank_2	1.000000	1.000000	0.000000	1.000000	1.000000
Bank_3	1.000000	1.000000	0.000000	1.000000	1.000000
Bank_4	1.000000	1.000000	0.000000	1.000000	1.000000
Bank_5	1.000000	1.000000	0.000000	1.000000	1.000000
Bank_6	1.000000	1.000000	0.000000	1.000000	1.000000
Bank_7	1.000000	1.000000	0.000000	1.007062	1.003374
Bank_8	1.000000	1.000000	0.000000	1.002296	1.001125
Bank_9	0.898618	1.000000	11.666667	0.898618	0.949104
Bank_10	0.888639	1.000000	0.000000	0.888639	0.942741
Bank_11	0.831909	0.846154	71.666667	0.831909	0.911531
Bank_12	0.839518	0.849624	71.666667	0.839518	0.913587
Bank_13	0.848988	0.852941	71.666667	0.848988	0.916852
Bank_14	0.858049	1.000000	0.000000	0.858049	0.920117
Bank_15	0.840800	0.841549	85.000000	0.840800	0.908476
Bank_16	0.738916	0.793103	120.000000	0.738916	0.846732
Bank_17	0.742242	0.797297	120.000000	0.742242	0.845554
Bank_18	0.747363	0.801325	108.333333	0.747363	0.845554
Bank_19	0.752285	0.870130	68.333333	0.752285	0.845554
Bank_20	0.757018	1.000000	0.000000	0.757018	0.845554
Bank_21	0.715647	0.718750	170.000000	0.715647	0.815804
Bank_22	0.722621	0.723926	170.000000	0.722621	0.816952
Bank_23	0.729343	1.000000	5.000000	0.729343	0.818101
Bank_24	0.644970	0.644970	205.000000	0.644970	0.757085
Bank_25	0.651163	0.651163	205.000000	0.651163	0.757085
Bank_26	0.657143	0.657143	205.000000	0.657143	0.757085
Bank_27	0.662921	0.662921	205.000000	0.662921	0.757085
Bank_28	0.630525	0.668508	213.333333	0.630525	0.729251
Bank_29	0.636549	0.755435	155.000000	0.636549	0.729251
Bank_30	0.642380	1.000000	0.000000	0.642380	0.729251
Bank_31	0.569201	0.578947	276.666667	0.569201	0.668616
Bank_32	0.578528	0.585492	276.666667	0.578528	0.670672

Table 3. Continued.

DMU	CCR	BCC	Eff_AP	Eff_Maj	Eff-1
Bank_33	0.589094	0.591837	276.666667	0.589094	0.673937
Bank_34	0.599341	0.698492	205.000000	0.599341	0.677202
Bank_35	0.554455	0.554455	310.000000	0.554455	0.635628
Bank_36	0.560976	0.560976	310.000000	0.560976	0.635628
Bank_37	0.567308	0.567308	310.000000	0.567308	0.635628
Bank_38	0.574132	1.000000	0.000000	0.574132	0.636202
Bank_39	0.541364	0.626168	273.333333	0.541364	0.602639
Bank_40	0.547704	0.723502	205.000000	0.547704	0.602639
Bank_41	0.485795	0.488636	385.000000	0.485795	0.542004
Bank_42	0.492713	0.495516	385.000000	0.492713	0.542004
Bank_43	0.499859	0.502212	385.000000	0.499859	0.542381
Bank_44	0.507650	0.508734	385.000000	0.507650	0.543529
Bank_45	0.515239	0.612069	302.500000	0.515239	0.544678
Bank_46	0.489362	0.489362	410.000000	0.489362	0.514170
Bank_47	0.495798	0.495798	410.000000	0.495798	0.514170
Bank_48	0.456432	0.502075	418.333333	0.456432	0.469636
Bank_49	0.456674	0.508197	406.666667	0.456674	0.463274
Bank_50	0.458502	0.635628	310.000000	0.458502	0.451844

According to *Table 3*, some educational centers, such as Bank_1 to Bank_8, have CCR and BCC scores equal to 1. This argument indicates that these centers are highly efficient relative to other centers and perform optimally across inputs and outputs. The Eff_Maj indicator for these centers is also close to 1, indicating stable performance.

Several other educational centers, such as Bank_9 to Bank_19, have CCR values less than 1, indicating relative inefficiency. These centers can improve their efficiency through better resource allocation and cost management. The Eff_AP index for some of these centers is quite high, showing significant potential for performance improvement. Medium-level educational centers, such as Bank_21 to Bank_34, have CCR and BCC values between 0.5 and 0.7. These centers demonstrate that with managerial improvements and resource optimization, they can approach the efficiency level of the most efficient centers. For these centers, the difference between Eff_AP and Eff_Maj is significant, indicating how different DEA methods can yield varying efficiency assessments.

Some low-performing educational centers, such as Bank_41 to Bank_50, have CCR and BCC scores below 0.5 and very high Eff_AP values. It indicates that these centers are highly inefficient and require management improvement programs and cost-reduction strategies to achieve a reasonable performance level. Eff-1 for these centers is low, highlighting poor overall performance. Overall, DEA results provide a clear distinction between efficient and inefficient educational centers, helping bank managers define optimal resource allocation and productivity strategies. Efficient centers can serve as benchmarks for others, while inefficient centers can implement corrective plans based on an analysis of the causes of inefficiency.

5 | Conclusion

The analysis of the educational centers demonstrated that several units operate at full efficiency, utilizing their resources optimally and delivering balanced educational outcomes. DEA proved to be an effective tool for evaluating the relative efficiency of these centers, providing benchmarks for best practices and supporting informed managerial decisions.

Some centers showed relative inefficiency, highlighting that factors beyond resource allocation—such as staff motivation, personnel funding, and job satisfaction—play a crucial role in educational performance. Effective management of these human and financial factors, alongside proper resource optimization, can enhance both staff satisfaction and the quality of educational services.

Centers with lower efficiency require targeted managerial attention and strategic planning to improve performance. For future research, incorporating fuzzy data could offer a more nuanced assessment of educational centers, accounting for subjective factors such as staff motivation and satisfaction. Overall, DEA combined with consideration of human and financial factors provides a robust framework for improving efficiency and guiding strategic decisions in educational institutions.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

Funding

This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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