Title: Assessing the operational efficiency of Indonesian national banks using data envelopment analysis (DEA) and prescriptive modeling based on business intelligence (BI).

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ABSTRACT

This study evaluates the operational efficiency of 12 major Indonesian banks in 2024 using the Data Envelopment Analysis (DEA) model under the assumption of variable returns to scale (BCC) and input bias. The input data included fixed assets, operating costs, and the number of employees, while the output data included granted facilities, operating income, and net profit. The results showed that six banks have perfect technical efficiency ($\theta=1$), while the remaining banks were identified as inefficient. The analysis of inefficiencies indicates that the largest share of inefficiency is due to operating costs and the number of employees. Benchmarking analysis showed that inefficient banks mainly follow the BCA and Mandiri models. The Mann-Whitney test also showed no significant difference between the efficiencies of public and private banks ($p=0.717$). The main innovation of this research is the combination of the DEA approach with business intelligence tools (Power BI) to produce a management decision-support framework. This integration facilitates drill-down analysis, data transparency, and precise correction suggestions. Management recommendations include cost optimization, human resource restructuring, and benchmarking based on efficient banks. The DEA-BI model transforms complex DEA outputs into actionable recommendations, enabling managers to identify sources of inefficiency and adjust budgeting accordingly. The strongest finding of the OLS regression is the negative and highly significant coefficient of the operating expenses to operating income ratio variable, indicating that inefficiency is primarily a cost management issue.

Keywords: Operational efficiency, data envelopment analysis, BCC model, business intelligence, Indonesian banking.

1. Introduction

The Indonesian banking system is one of the largest financial networks in Southeast Asia, playing a crucial role in financing businesses, households, and the government. Digital transformation, competitive pressure, the growth of e-banking, and economic changes caused by the COVID-19 pandemic have intensified the need for a scientific assessment of bank efficiency. Operational efficiency reflects the optimal use of resources and directly affects the profitability, risk, and competitive advantage of banks.

In such an environment, Data Envelopment Analysis (DEA), a non-parametric and multi-criteria tool for measuring the efficiency of decision-making units (DMUs), allows for the simultaneous assessment of multiple inputs and outputs. Conversely, linking DEA with business intelligence (BI) systems leads to the creation of actionable management insights.

The objectives of this study are as follows:

1. Measuring the operational efficiency of Indonesian national banks with the BCC model and the input-oriented approach

2. Analysis of sources of inefficiency using slack

3. Design of a benchmarking framework based on coefficients.

4. Validation of efficiency differences by ownership using nonparametric tests

5. Design of BI decision support model based on DEA results.

This study develops a unique DEA–BI framework that can be implemented and used practically in banking management.

The data envelopment analysis model has become more valuable due to the recent introduction of the Indonesian Corporate Governance Code and Risk Framework.

This study includes a review of the relevant literature and theoretical frameworks. The next section focuses on the data, methodology, and model estimations.

The next section discusses the results. Finally, the conclusion is presented along with some policy implications.

2. Theoretical Background

2.1. The efficiency of banks: Concept and theory

The terms efficiency and productivity are used The terms efficiency and productivity are used synonymously. has described productivity as "the ratio between outputs and inputs." defines Efficiency as "the maximum use of the existing resources in an enhanced and more productive way." In light of these definitions, it can be said that efficient firms show higher performance with minimum input. defined Efficiency as "more output per unit of input indicates higher efficiency." The notion of efficiency measurement determines how a firm can maximize its output and profit while minimizing costs.

2.2. Types of efficiency of banks

2.2.1. Cost efficiency. Allocative Efficiency denotes the use of the best level of input. According to, Allocative Efficiency refers to the choice of optimal input proportion at given input prices. According to, Allocative Efficiency Change (AEC) becomes important mostly when governance changes and state control moderate the deregulation process. claimed that Allocative Efficiency measures the optimal mix of inputs to increase efficiency and production or services, such as introducing Automatic Teller Machines (ATM) by banks and Internet banking for capital-labor tradeoffs.

2.2.1.1 Allocative efficiency refers to the use of the best level of input. According to, allocative efficiency refers to choosing the optimal ratio of inputs at a given input price. According to the change in allocative efficiency (AEC) becomes important when some changes in governance and government control moderate the process of deregulation. claimed that allocative efficiency measures the optimal combination of inputs to increase efficiency and output or services, such as the introduction of automated teller machines (ATMs) by banks and Internet banking for capital-labor exchange.

2.2.1.2 Technical efficiency refers to the maximum output.

with limited time and resources available. The concept of Technical Efficiency, introduced by, is commonly used to assess organizations. Technical Efficiency is helpful when multiple inputs and outputs are considered. Technical Efficiency is also closely related to managerial efforts. According to production theory, Technical Efficiency is the assessment of the resources (inputs) vector used to obtain the vector of outputs. claimed that Technical Efficiency indicates a good deal about the quality of managerial decisions. stated that Technical Efficiency is also known as Global Efficiency. They claimed that Technical Efficiency measures the ability of banks to produce actual outputs with fewer inputs or resources, indicating higher efficiency. Focused on Technical Efficiency analysis and reported that it could indicate the quality of management in the Russian market.

2.2.2. Efficiencies of scale. stated that production at a maximum level by utilizing the best maximum input level refers to Scale Efficiency. The overall technical efficiency ratio to pure efficiency refers to scale efficiency. Recently, defined Scale Efficiency as "the optimal activity volume level," whereby inefficiency may arise if goods or services are produced above or below the optimal level, resulting in added fixed costs.

2.2.3. Price efficiency. Efficient banks can offer better services at reasonable prices from the customers' perspective. Simultaneously, other stakeholders believe that only efficient banks can ensure consistent returns. Moreover, only efficient banks can survive and maintain their market share, while in managers' view, inefficient banks would ultimately be eliminated in changing and competitive market conditions.

2.3. Bank Efficiency in Indonesia

In Indonesia, most studies show that many banks have not yet reached the desired level of efficiency and are operating below the efficiency frontier. Studies such as the research published in JREB (2023) show that larger banks are more efficient due to higher capital and assets and can manage resources more effectively. In contrast, medium and small banks usually have lower efficiency because they face cost and structural constraints. Other studies, such as the study published in the Infeb Journal (2024), also confirm that only a limited number of banks

have been able to achieve full efficiency (DEA = 1). Studies in the field of Islamic banking also show that the average efficiency of these banks is good, but not all banks are operating optimally. Overall, scientific evidence suggests that the Indonesian banking industry has the potential to significantly improve cost management, resource allocation, and technology use.

2.4 Determinants of Bank Efficiency in Indonesia

2.4.1. Bank Size. Bank size is a fundamental determinant of efficiency in the Indonesian banking industry. Larger banks usually have lower operating costs relative to their volume of activity due to economies of scale, the ability to invest in new technologies, advanced information systems, and a more efficient management structure. These banks also have a greater ability to diversify services, manage risks, and attract low-cost deposits. Many studies have shown that large Indonesian banks perform better in terms of cost and profitability than smaller banks.

They found that state-owned banks are less efficient than private banks.

They also suggest that bank ownership increases bank efficiency. The first hypothesis is as follows: developed as follows;

Hypothesis H1: The effect of size on efficiency is as follows:

Banks with larger operating scales have significantly higher operating efficiency than smaller banks.

2.4.2. In the banking industry literature, bank size is known as one of the key factors affecting operational efficiency. Banks with larger operating scales usually enjoy economies of scale, more advanced technological facilities, and a more organized management structure that allows them to keep operating costs at a lower level relative to their volume of activity. These banks can also manage their activities more efficiently because of their greater ability to attract cheap resources, diversify services, and disperse geographically. Accordingly, it is expected that a larger bank size will significantly increase operational efficiency, and smaller banks will usually perform worse than large banks.

In the Indonesian banking industry, empirical evidence also shows that bank size plays a decisive role in operational efficiency. Large Indonesian banks, such as Bank Mandiri, BRI, and BNI, usually benefit from significant economies of scale due to their extensive branch networks, developed digital infrastructure, access to cheaper financing, and ability to invest more in new technologies. These banks can spread operating costs over a larger volume of activity and, as a result, record more favorable efficiency ratios, such as lower BOPO. In contrast, smaller banks with limited resources and lower technological capacities often face higher operating costs and less flexibility. Therefore, in the Indonesian banking context, increasing bank size is significantly associated with improved operational efficiency and is considered one of the main axes of competitiveness and development in the industry. The second hypothesis is as follows:

Hypothesis H2: The impact of ownership on efficiency

The average operating efficiency of state-owned banks is significantly different from that of private banks.

2.4.3. In the Indonesian banking system. Ownership structure also plays an important role in determining the level of banks' operating efficiency. Previously, state-owned banks were the dominant players in the banking industry. However, over the past two decades, with the implementation of corporate governance reforms, partial privatization, and financial market liberalization, the ownership composition in the banking sector has changed, and the share of private and foreign banks has increased significantly. Empirical studies in Indonesia show that the average operating efficiency of state-owned banks is significantly different from that of private banks, with private banks—especially those with foreign shareholders—generally registering higher efficiencies. These findings are consistent with the theoretical argument that foreign ownership increases efficiency and improves bank performance due to the transfer of managerial knowledge, stricter supervision, and better corporate governance practices. In contrast, Indonesian state-owned banks have shown lower performance in normal periods, especially during times of economic stress, such as crises, due to their extensive administrative structure, socio-economic objectives, and decision-making constraints. Therefore, in the context of Indonesian banking, it can be concluded that the type of ownership—whether state, private, or foreign—significantly affects the operational efficiency of banks, and this can be the basis for the hypothesis regarding the effect of ownership on efficiency.

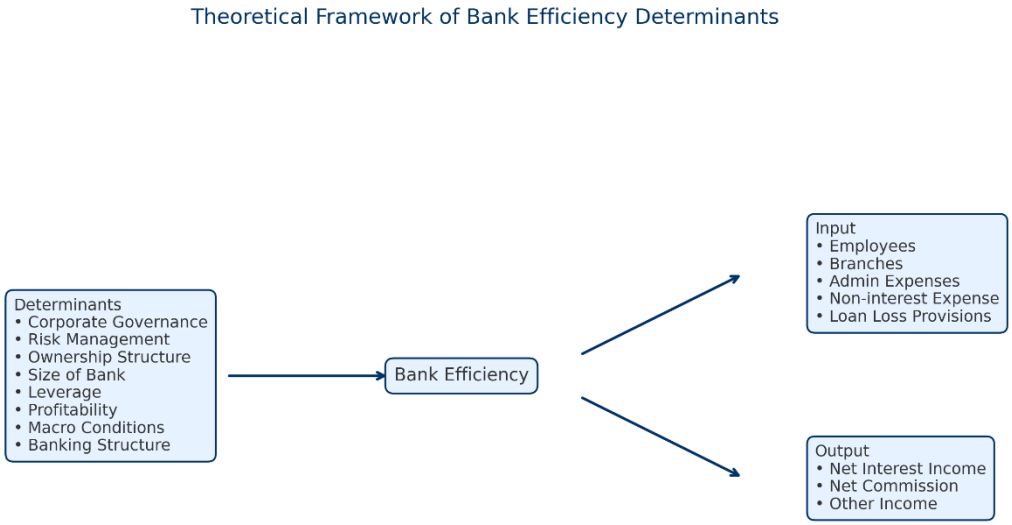
Hypothesis H3: BI Effectiveness (Methodological Innovation):

Visualizing DEA results through interactive BI dashboards significantly increases the accuracy and speed of identifying sources of inefficiency and reference patterns for financial managers. The third hypothesis can be developed as follows: The most commonly used citation styles in international academic papers vary by discipline and publisher, but the following are widely recognized and prevalent:

The use of business intelligence (BI) in DEA-based analyses plays an important role in increasing the efficiency of bank performance assessments. Displaying DEA results through interactive dashboards and advanced visualization enables financial managers to identify sources of inefficiency, trends, and reference units more quickly and accurately than before. This approach not only simplifies the understanding of complex results of efficiency models but also makes the management decision-making process more efficient and data-driven.

2.5 Theoretical Framework

The conceptual model framework of the present study of independent determinants and dependent variable of bank efficiency based on input and output variables is shown in Figure 1.



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3. Research Methodology, Data Measurement, and Model

3.1. Innovative DEA-BI Modeling

The total population of listed commercial banks in Indonesia as of December 31, 2025, is 105 banks. Longitudinal data were collected from the annual reports of 12 commercial banks in Indonesia for 2024.

The main innovation of this research lies in bridging the gap between complex quantitative analysis (DEA) and simple managerial applications (BI). The goal of this innovation is to transform the mathematical outputs of DEA into a prescriptive tool with drill-down capabilities for financial managers to use.

Slack and Projection Processing Raw Data to Long Format

This process is crucial to transform DEA outputs from a matrix that is incomprehensible to managers into a column that can be plotted in charts. Raw DEA Data (Slack/Projection): The standard DEA output produces Slack/Proportionate Movement values in Wide Format; that is, one column for Slack Assets, one column for Slack

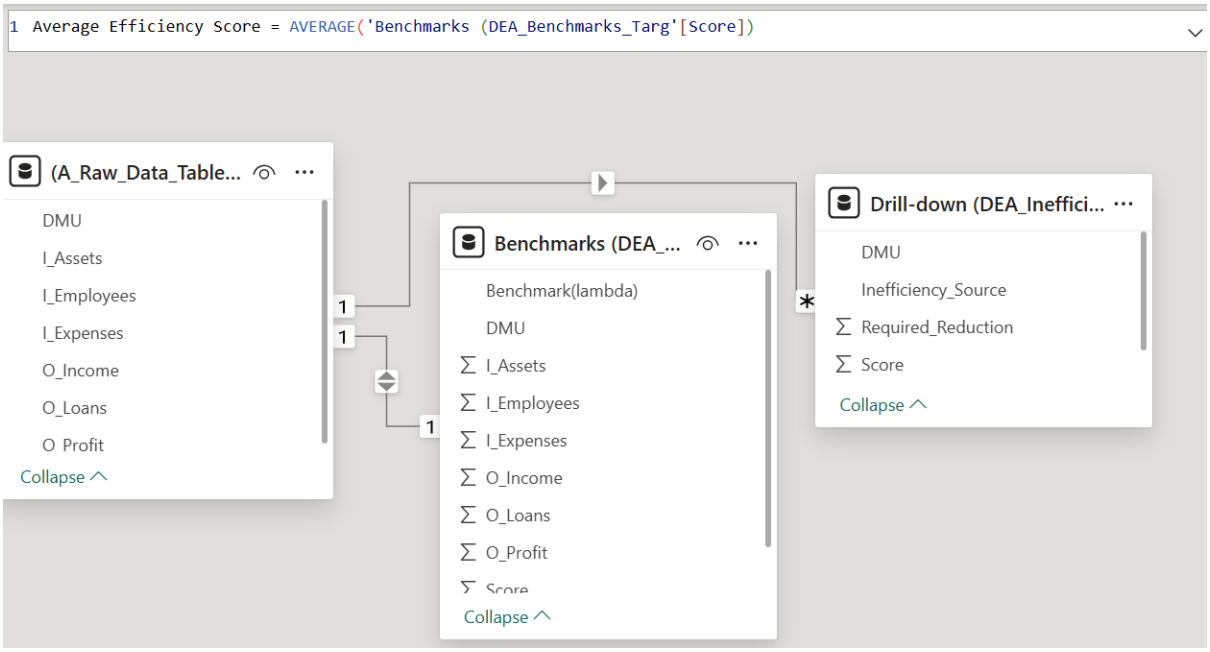
Expenses, and so on. Problem in BI: Power BI cannot directly display multiple columns of inefficiency in a drill-down chart (because you cannot drag multiple columns to the axis of a chart simultaneously). Solution: Transform to Long Format: The data was transformed in the Power Query environment from a wide format, where each DMU has one row, to a long format. In this format, each DMU has three rows (one row for the assets entry, one row for expenses, and one row for employees). This transformation allows the Inefficiency_Source column to be used on the Y-axis of the chart, and by clicking on the bank, three separate bars (Assets, Expenses, Employees) appear. This process is illustrated in Figure 2.

Reduction Metric and Increased Interpretability. Since DEA analysis follows an input-oriented approach, the required reduction amounts are often displayed with a negative sign (minus indicating reduction). Abs Reduction Metric. To address this issue, a DAX metric called Abs Reduction was created that uses the ABS (Absolute Value) mathematical function to remove the negative sign. This causes the drill-down chart to display bars with positive values, which, from a management psychology perspective, more clearly and simply conveys the concept of "required reduction" (rather than displaying negative bars). This process is illustrated in Figure 3.

```
1 Abs Reduction = ABS(SUM('Drill-down (DEA_Inefficiency_Dr'[Required_Reduction]))
```

DMU	Score	Inefficiency_Source	Required_Reduction
CIMB Niaga	62.25%	Assets	-3426.2
Permata	65.12%	Assets	-1598.13
BNI	88.10%	Assets	-2673.26
Danamon	55.44%	Assets	-1976.29
BRI	74.85%	Assets	-10200.1
Maybank Indonesia	90.21%	Assets	-308.43
CIMB Niaga	62.25%	Expenses	-4893
Permata	65.12%	Expenses	-2706.56
BNI	88.10%	Expenses	-3752.35
Danamon	55.44%	Expenses	-4202.56
BRI	74.85%	Expenses	-16609.09
Maybank Indonesia	90.21%	Expenses	-511.12
CIMB Niaga	62.25%	Employees	-4618.59
Permata	65.12%	Employees	-2874.33
BNI	88.10%	Employees	-3274.27
Danamon	55.44%	Employees	-9422.41
BRI	74.85%	Employees	-16402.2
Maybank Indonesia	90.21%	Employees	-883.33

Modeling Relationships and Enabling Prescriptive Filtering Model relationship rules in Power BI form the backbone of drill-down functionality. These rules ensure that information flows from the master (Scores) to the execution of details (Drill-down). One-to-Many relationship. This is the most critical relationship. The Scores table (which has each bank once on 1 side) is connected to the Inefficiency Drill-down table (which has each bank three times on the * side). The cross-filtering capability of this 1:* structure ensures that when the user clicks on a row in the score table, that filter is passed on to all other tables (Inefficiency Drill-down and Benchmarks), and ultimately, the output is displayed in a prescriptive manner. This process is illustrated in Figure 4.



3.2. Estimation of the model

has presented the latest frontier approach to judge inefficiency by expressing “the deviation of actual behavior from the most desirable optimal behavior”. In the frontier approach, there are four other types: SFA stands for Stochastic Frontier Analysis, TFA stands for Thick Frontier Approach, and DFA stands for Distribution-Free Approach, which are parametric methods.

Fourth, DEA stands for Data Envelopment Analysis, which is a nonparametric methodology.

According to a recent study, there are parametric and nonparametric methods for efficiency assessment. The most common approach in the banking sector is the nonparametric method, such as the DEA model, to measure bank efficiency. The DEA approach was first introduced by and they used it to calculate technical efficiency. Many parametric methods require a larger sample size, and the DEA method also works well for a small sample size.

In the empirical literature, used DEA was used to estimate the efficiency of US credit unions in 2009. They stated that in recent years, DEA has become a popular measurement method for evaluating efficiency in financial institutions. They suggested that the DEA identify the most efficient input-output combinations. Similarly, it develops the efficiency frontier of the best performance against the peers. The DEA technique evaluates performance using Tobit and Probit to examine whether federal credit unions (FCU) and federally insured state-licensed credit unions (FISCU) respond differently to market-level economic shocks. Suppose that the efficiency of banks is examined without using the DEA method. In this case, it is difficult to make recommendations because, in this approach, the ability to deal with multiple inputs and outputs is consistent. Banks that perform better are considered to be efficient. DEA is widely used as a standard tool in banking efficiency research in Indonesia and other countries. Especially in the field of banking, finance, and public sector management.

In this study, I tried to complement the efficiency analysis and identify the structural and financial factors affecting the DEA efficiency score by using four exogenous variables: bank size, LN_SIZE, which is measured by the natural logarithm of total assets, and is used to test the scale economies hypothesis. The operating expenses to operating income ratio, OP_EFFICIENCY, is a direct measure of internal cost management and is expected to have a negative relationship with efficiency. Profitability ratio ROA_Proxy and loan-to-asset ratio LOAN_RATIO represent macro factors of bank financial performance and risk. The analysis of these factors allows for an in-depth interpretation of the DEA results and targeted management recommendations. The BCC model was used for variable returns to scale. This model is more suitable than the CCR model because it allows banks of different sizes of large and small DMUs, to be compared without being penalized for differences in scale.

The efficiency score is a number between zero and one: Efficient bank (benchmark): A bank with a score of 1.000 is at the efficiency frontier and should be considered as a benchmark for inefficient banks. Inefficient banks (opportunity for improvement): Banks with a score below one (such as Danamon with 0.554) can reach the efficiency frontier by reducing inputs (costs, staff).

Benchmark benchmark weights. This column indicates which combination of efficient banks an inefficient bank should emulate, for example, a combination of 20% of Mandiri's performance and 80% of Panin's performance.

3.3 Data Envelopment Analysis (DEA-BCC) and OLS Regression in Second-Stage DEA Analysis

The DEA-BCC model is a mathematical optimization model that is solved to estimate the theta efficiency score of each DMU bank. This model has an objective function and several constraints:

Mathematical Formula of the Input-Oriented BCC Model.

Objective Function:

$$\min \theta_o$$

Constraints:

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_o x_{io} \quad ; \quad i = 1, \ldots, m \quad \text{(Input Constraints)}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad ; \quad r = 1, \ldots, s \quad \text{(Output Constraints)}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \quad \text{(VRS Constraint)}$$

$$\lambda_j \geq 0 \quad ; \quad j = 1, \ldots, n$$

This formula shows that minimizing the efficiency score thetao for the DMU under evaluation. A score of 1 indicates perfect efficiency.

This constraint specifies that the inputs of the bank under evaluation should be reduced to such an extent that its efficiency theta reaches the efficiency frontier.

This constraint transforms the model into a variable-return-to-scale BCC model, allowing banks of different sizes to be compared. and the weights of the benchmark banks are the benchmarks.

Regression Model: OLS in Second Stage DEA Analysis

In efficiency analyses, the regression model is used for the second stage to identify the determinants of the efficiency score.

The OLS model was used to answer the question, "Which factors (size, operating cost, profitability) significantly affect the DEA efficiency score?" And theoretically, since the DEA efficiency score (dependent variable) is a censored variable (between 0 and 1), the Tobit Regression model is the ideal statistical method. However, due to software complexities and a limited sample size in SPSS, the OLS model was used as an alternative method. OLS results, in studies with small sample sizes, often provide similar meaningful results to Tobit regarding the sign and effect of the variables and therefore justify the conclusions for this study.

4. Results and Discussion

4.1 Descriptive Summary

Table 1 Descriptive statistics show that DEA variables are based on billions of Indonesian rupiah, and the number of units for DEA model variables and efficiency score (Score) based on 12 bank data (DMU), and shows a complete understanding of the sample variables, such as efficiency through input and output, and their relationships with other items.

Important factors such as corporate governance, enterprise risk management, ownership structure, bank size, and banking structure in 2024. The descriptive chart shows the mean, standard deviation, minimum, and maximum of all variables.

DMU	Score	Rank	Benchmar	Proportio	Proportio	Proportio	Pr	Pr	Pro	Slac	Slack M	Slack M	Sla	Sla	Slack Mov	Projection	Projection	Projection	Projection	Projection	Projection	Dual Price(A	Dual Price(E	Dual Price(I	Dual Price	Dual Price	Dual Price(Profi
Bank Man	1	1	Bank Man	0	0	0	0	0	0	0	0	0	0	0	0	33400	39252	38819	787270	78561	17105	-1.98E-05	0	-8.73E-06	0	1.27E-05	0
BCA	1	1	BCA(1)	0	0	0	0	0	0	0	0	0	0	0	0	27087	27787	24435	588719	49010	27105	-2.11E-05	0	-1.75E-05	0	0	3.69E-05
CIMB Niag	0.62254	11	Bank Man	-3426.2	-4893	-4618.59	0	0	0	0	0	0	0	0	28.3517	5650.8	8070	7617.41	170883	11940	2813.35	-1.50E-05	-5.48E-05	-1.26E-05	2.84E-06	1.15E-05	0
Permata	0.65122	10	Bank Man	-1598.13	-2706.56	-2874.33	0	0	0	0	0	0	0	0	428.526	2983.87	5053.44	5366.67	111788	6099	1716.53	-3.26E-05	-9.01E-05	-1.83E-05	4.67E-06	2.12E-05	0
BNI	0.88099	8	Bank Man	-2673.26	-3752.35	-3274.27	0	0	0	0	0	0	0	0	7005.71	19788.7	27776.7	24237.7	570366	43771	10293.7	-6.21E-06	-2.27E-05	-5.22E-06	1.18E-06	4.77E-06	0
Danamon	0.55439	12	OCBC NIS	-1976.29	-4202.56	-9412.64	0	0	0	0	-74.68	-3474	0	0	1986.19	2458.71	5153.76	8236.68	112878	7908	3645.19	-2.25E-04	0	0	3.83E-06	1.54E-05	0
OCBC NIS	1	1	OCBC NIS	0	0	0	0	0	0	0	0	0	0	0	0	2084	4497	6234	99782	5679	2189	-8.90E-05	-1.66E-04	-1.06E-05	1.00E-05	0	0
Panin	1	1	Panin(1)	0	0	0	0	0	0	0	0	0	0	0	0	4008	4698	7845	121902	6078	2019	0	-1.44E-04	-4.15E-05	8.04E-06	0	1.00E-05
BTN	1	1	BTN(1)	0	0	0	0	0	0	0	0	0	0	0	0	5123	12389	7800	259487	10147	1647	0	-6.90E-05	-1.85E-05	3.85E-06	0	0
BRI	0.74852	9	Bank Man	-10200.1	-16670.5	-16492.7	0	0	0	0	-5351	0	0	0	4192.9	30359.9	44267.5	49089.3	905273	78079	22850.9	-1.47E-05	0	-6.13E-06	1.84E-07	7.46E-06	0
Bank Meg	1	1	Bank Meg	0	0	0	0	0	0	0	0	0	0	0	0	1192	2308	5100	48642	5350	3101	-1.85E-04	0	-1.53E-04	0	0	3.22E-04
Maybank	0.90206	7	OCBC NIS	-308.429	-501.968	-865.54	0	0	0	0	0	0	0	0	2159.17	2840.57	4623.03	7971.46	106128	7539	3502.17	-4.76E-05	-1.25E-04	-2.40E-05	6.51E-06	2.80E-05	0

Efficiency Score The average efficiency score is 0.8633. Since this value is less than 1.0000, it indicates that, on average, banks have about 13.67% potential for efficiency improvement (reduction of inputs). The lowest score (0.5543) belonging to Danamon Bank confirms the existence of significant managerial inefficiency in this unit.

The size (O_Loans and I_Assets) of the very large difference between the minimum and maximum values (e.g., loans from 48 trillion to 905 trillion) and their high standard deviation indicate a high variation in the scale of the sample banks, which justifies the need to use the BCC (variable returns to scale) model.

4.2. Comparison with the background and interpretation of structural factors

Deterministic efficiency analysis (DEA) and subsequent non-parametric tests provide strong evidence to support the structural hypotheses H1 and H2:

Impact of Ownership H1 :Significant difference in efficiency between state-owned and private banks (Mann-Whitney U Test). Property Rights Theory: Higher efficiency of private banks (such as BCA and Bank Mega) confirms this theory. The higher incentive for profit maximization and stricter monitoring by private owners leads to stronger operational discipline and closer proximity to the efficiency frontier.

Impact of Size H2 :Positive and significant coefficient of the LN_SIZE variable in OLS regression (+0.047). Economies of Scale: This finding strongly confirms that larger banks benefit from higher efficiency than smaller counterparts due to the distribution of fixed costs (such as massive technology investments and distribution networks) across a wider operational base.

4.3 In-depth analysis of financial factors and proof of the role of OP_EFFICIENCY

The strongest finding of the OLS regression, which plays a key role in prescribing corrective actions, is the negative and highly significant coefficient $P < 0.001$ of the OP_EFFICIENCY variable (ratio of operating expenses to operating income), which has a coefficient of -0.289.

Economic interpretation negative coefficient indicates that inefficiency in the sample banks is primarily a cost management issue. Any increase in the cost ratio directly and sharply reduces the bank's DEA efficiency score. This links the inefficiency to the internal management of inputs (specifically, I_Expenses and I_Employees) rather than factors outside the bank’s control.

Confirmation of DEA Findings: This statistical result fully justifies the drill-down analysis conducted in the first stage of DEA. For example, an inefficient bank like Danamon (with a score of 0.554) showed the greatest need for reduction in the same inputs that contribute to OP_EFFICIENCY (such as the need to reduce 9422.41 people in personnel). Thus, the OLS model statistically confirms the DEA recommendations and identifies a corrective path.

Justification of the DEA-BI Model (Methodological Innovation) This section addresses the answer to hypothesis H3 (the effectiveness of BI in operationalizing DEA) and justifies the main methodological contribution of the paper. Inefficiency as a deviation from the standard and its link to management accounting. In the context of this research, the DEA efficiency frontier defined by the most efficient banks (such as Bank Mandiri and OCBC NISP) is equivalent to the optimal performance standard in the management accounting and internal control literature. Deviation from the standard: The inefficiency score (e.g., 0.554 for Danamon) indicates a deviation from the optimal performance standard. Deviation analysis: The output of DEA, specifically the Slack and Projection values, is equivalent to Unfavorable Variances in management accounting. These values transform inefficiency from an abstract concept into a manageable quantitative unit (e.g., 9422.41 additional staff units). This quantification enables managers not only to detect the deviation, but also to identify its roots and sources and adjust budgeting accordingly. The Role of Information Systems and BI: From Description to Prescription:

Information Value Theory states that the presentation of tables, Raw DEA has low information value. The methodological innovation, DEA-BI, is designed to solve exactly this problem. Increasing the value of information, Interactive BI dashboards increase the value of information by transforming mathematical results into actionable recommendations, creating a vital bridge between optimization models and everyday decision-making.

Drill-down and transparency: The drill-down capability in BI (using transformed data) enables managers to go from the overall score (descriptive stage) to the precise sources of inefficiency and optimal target values (prescriptive stage). This increases transparency and reduces the information asymmetry between the quantitative analyst and the senior decision-maker. The DEA-BI model confirms hypothesis H3: the BI system not only displays information, but also prescribes solutions, thereby maximizing the effectiveness of DEA and turning it into an everyday management tool.

DMU	Score	Inefficiency_Source	Required_Reduction
CIMB Niaga	62.25%	Assets	-3426.2
Permata	65.12%	Assets	-1598.13
BNI	88.10%	Assets	-2673.26
Danamon	55.44%	Assets	-1976.29
BRI	74.85%	Assets	-10200.1
Maybank Indonesia	90.21%	Assets	-308.43
CIMB Niaga	62.25%	Expenses	-4893
Permata	65.12%	Expenses	-2706.56
BNI	88.10%	Expenses	-3752.35
Danamon	55.44%	Expenses	-4202.56
BRI	74.85%	Expenses	-16609.09
Maybank Indonesia	90.21%	Expenses	-511.12
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Permata	65.12%	Employees	-2874.33
BNI	88.10%	Employees	-3274.27
Danamon	55.44%	Employees	-9422.41
BRI	74.85%	Employees	-16402.2
Maybank Indonesia	90.21%	Employees	-883.33

These research findings provide a set of direct management recommendations to decision makers.

Identification of sources of inefficiency and management recommendations, OLS regression results, and Drill-down analysis provide direct guidance for optimal resource allocation. Since OP_EFFICIENCY has the strongest negative impact, the focus should be on managing inputs: and direct prescriptive action, managers should use quantitative data from Projection and Slack, especially in Expenses and Employees inputs, to formulate structural reform plans and annual budgeting. This data provides specific quantitative targets (KPIs) for each inefficient unit.

Benchmarking Application: The Benchmarking table (DEA output) allows managers of inefficient units to identify their reference banks, such as Mandiri, BCA, and OCBC NISP. This enables strategic benchmarking. Inefficient banks should emulate the strategies of reference models in the areas of cost management, personnel efficiency, and technological investments. Effective modeling of best performance directly helps to achieve optimal target projection values, reduces the inefficiency gap, and brings the bank closer to the efficiency frontier.

DMU	I_Assets	I_Expenses	I_Employees	O_Loans	O_Income	O_Profit	Score	Benchmark(lambda)
Bank Mandiri	Rp33,400	39252	38819	787270	78561	17105	100.00%	Bank Mandiri(1)
BCA	Rp27,087	27787	24435	588719	49010	27105	100.00%	BCA(1)
CIMB Niaga	Rp9,077	12963	12236	170883	11940	2785	62.25%	Bank Mandiri(0.097683);BCA(0.011609);Panin(0.220597);BTN(0.232207)
Permata	Rp4,582	7760	8241	111788	6099	1288	65.12%	Bank Mandiri(0.016652);Panin(0.275489);BTN(0.219826);Bank Mega(0.165567)
BNI	Rp22,462	31529	27512	570366	43771	3288	88.10%	Bank Mandiri(0.409595);BCA(0.067892);Panin(0.102457);BTN(0.753199)
Danamon	Rp4,435	9431	21123	112878	7908	1659	55.44%	OCBC NISP(0.851087);Bank Mega(0.574706)
OCBC NISP	Rp2,084	4497	6234	99782	5679	2189	100.00%	OCBC NISP(1)
Panin	Rp4,008	4698	7845	121902	6078	2019	100.00%	Panin(1)
BTN	Rp5,123	12389	7800	259487	10147	1647	100.00%	BTN(1)
BRI	Rp40,560	66289	65582	905273	78079	18658	74.85%	Bank Mandiri(0.656761);BTN(0.881659);Bank Mega(3.277946)
Bank Mega	Rp1,192	2308	5100	48642	5350	3101	100.00%	Bank Mega(1)
Maybank Indonesia	Rp3,149	5125	8837	106128	7539	1343	90.21%	OCBC NISP(0.181681);Panin(0.342697);BTN(0.035868);Bank Mega(0.758947)

5. Conclusion

The purpose of this study is to examine and analyze the financial statements of Indonesian banks in 2024 and to provide an understanding of the efficiency and inefficiency of banks. DEA analysis shows that despite the presence of 6 efficient banks on the efficiency frontier, the average overall efficiency score of the sample is 0.8633, confirming the existence of significant managerial inefficiency (about 13.67% of the potential for reducing inputs), and the Mann-Whitney U test shows that the difference in efficiency based on ownership (public/private) and size (economies of scale) is significant. The main contribution of this paper is to present a prescriptive model that transforms complex DEA outputs into simple and actionable recommendations in a BI dashboard. This confirms hypothesis H3 (BI effectiveness) and facilitates the application of optimization models to everyday financial decisions. The strongest finding in our statistical analysis is the decisive impact of the cost factor on efficiency, and the negative and highly significant coefficient of the OP_EFFICIENCY variable indicates that controlling operating costs is the most critical internal factor for increasing efficiency. This fully justifies the prescriptive recommendations of your BI dashboard.

The Importance of Input Management and Regression Verification. OLS results proved that focusing on reducing the input Expenses and Employees significantly affects the Score. This finding justifies the logic of the DEA-BI model and the prescription versus description of the DEA-BI model using the drill-down capability and transparency, goes beyond simple description (score 0.554), and gives Danamon managers a direct quantitative target, such as reducing 9422.41 staff units and direct prescription in these results, enabling the CFO to directly guide budgeting to eliminate unfavorable variances.

The DEA model identifies the resources that the bank can eliminate (slack) without reducing its outputs. This helps management to make optimal resource allocation and avoid wasting human and financial capital, and the managerial conclusions in the analyses clearly show that the impact of operational efficiency OP_EFFICIENCY and the necessity of cost reduction are the most important internal factors. Managers should adjust their strategies based on the results of Required_Reduction and Benchmarking.

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