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AN EFFICIENCY ANALYSIS OF LISTED HEALTHCARE PROVIDERS IN INDONESIA: A DATA ENVELOPMENT ANALYSIS APPROACH, 2018–2025

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Abstract

Hospital companies are capital-intensive organisations that must sustain service capacity while converting fixed assets and operating costs efficiently into revenue. This study measures the operational efficiency of six general hospital issuers listed on the Indonesia Stock Exchange—MIKA, SILO, HEAL, SRAJ, SAME, and PRIM—over 2018–2025. A pooled input-oriented Data Envelopment Analysis under the Variable Returns to Scale (VRS/BCC) assumption was applied, using net fixed assets, cost of revenue, and operating expenses as inputs and revenue as output, yielding 48 DMU-year observations evaluated against a single frontier. Variable suitability was verified through Grey Relational Analysis, isotonicity testing, and the coefficient of variation, after which Returns to Scale (RTS) and input slack were examined to locate the sources of inefficiency. The mean efficiency score was 0.86, rising from 0.85 in 2018 to 0.88 in 2025, with the highest annual mean of 0.93 in 2021. MIKA recorded the highest average score (0.96) and SRAJ the lowest (0.69). Net fixed assets were the most frequent source of slack (54.17 per cent of observations), followed by operating expenses (39.58 per cent), with the dominant source shifting from operating expenses during 2018–2021 to net fixed assets from 2022 onward. The findings indicate that the principal efficiency challenge for listed hospital issuers is not the magnitude of investment but the ability to utilise installed capacity and convert fixed assets into revenue; hospital management should therefore prioritise demand-matched capacity planning and utilisation monitoring over further asset expansion

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INTRODUCTION

The health sector is a priority of Indonesia's national development: Law Number 36 of 2009 requires the government to allocate at least five per cent of state expenditure to health, and hospitals absorb the dominant share, since 80 to 85 per cent of national health insurance funds finance advanced referral services delivered in hospitals rather than primary care. Under Regulation of the Minister of Health Number 3 of 2020, hospitals may be established by central government, regional governments, or the private sector, and growth has been most pronounced in the private segment: privately-operated general hospitals rose from 1,445 units in 2020 to 1,576 in 2024, outpacing the combined growth of regional government hospitals (773 to 881) and central government hospitals (230 to 253) and now forming roughly 58 per cent of all general hospitals in Indonesia.

This expansion has accompanied a shift in management paradigm towards business and efficiency principles. Hartono (2010) argues that the transformation of hospitals from social institutions into business entities follows logically from the increasing complexity of community health needs and the limited fiscal capacity of government, while Trisnantoro (2014) observes that progressive liberalisation of the health sector since decentralisation has driven substantial private investment in hospital provision. Expanding service capacity, however, also enlarges the resources that must be managed and the costs that must be recovered.

Private hospital expansion has coincided with sustained pressure on operating costs, driven in part by medical inflation. Indonesian medical inflation ranged between 12 and 13 per cent throughout 2019–2023, well above general inflation of two to five per cent over the same period. A significant driver is pharmaceutical prices, reflecting structural dependence on imported raw materials: an estimated 85 to 95 per cent of pharmaceutical raw materials are imported, and imports rose from USD 443 million in 2021 to USD 509 million in 2022 and USD 1.27 billion in 2023, leaving drug prices exposed to exchange-rate and commodity volatility.

Pressure on material inputs is accompanied by escalating labour costs of a different behavioural character. Specialist physician compensation is largely variable, moving elastically with patient volume under fee-for-service arrangements (Zelman et al., 2020). Non-specialist labour—nursing, medical support, and administration—behaves instead as a fixed cost that must be met irrespective of bed occupancy. Noreen and Soderstrom (1997) characterise these salaries as capacity costs incurred to maintain the minimum service capacity required for patient safety and operational legality, and therefore sticky, since they cannot be cut abruptly when volume declines given employment regulation and staffing standards.

Alongside cost pressure, the capital-intensive character of hospital services constitutes a distinct financial burden. Barniv, Danvers, and Healy (2000) note that health services require large capital investment in buildings, medical equipment, and supporting systems. Among listed hospital issuers, the ratio of net fixed assets to total assets for the three largest issuers rose from an average of 48.6 per cent in 2021 to 63.2 per cent in 2025. A high proportion of fixed assets translates into substantial depreciation recognised each period, and Roberts et al. (1999) show that hospitals continue to bear the fixed costs of asset ownership regardless of how far the corresponding capacity is actually used.

On the revenue side, participation in the National Health Insurance (JKN) programme carries its own consequences. Participating hospitals are bound by the Indonesia Case Based Groups (INA-CBGs) system, a package-based claim mechanism whose rates are set by government according to diagnosis and procedure groupings. Although designed to control costs, in practice it generates a negative gap between reimbursed claims and hospitals' actual tariffs (Raafiana & Andriani, 2025), while claim settlement timing constrains cash flow, with a substantial proportion of claims entering dispute cycles that delay payment by 30 to 90 days. Cost, revenue, and cash-flow pressures therefore operate simultaneously, compelling hospital companies to optimise resource management under progressively thinner margins.

These pressures are visible in the financial statements of listed general hospital issuers. Over 2018–2025 revenue grew steadily but was matched almost constantly by growth in cost of revenue and operating expenses, producing a stable and narrow nominal margin. The ratio of operating expenses to operating revenue (BOPO)

improved from 0.89 in 2018–2019 to a low of 0.79 in 2021, when revenue growth of 34.92 per cent outpaced expense growth, before reversing to 0.86 in 2022 as revenue contracted 5.54 per cent while costs kept rising—confirming the sticky character of the cost structure. BOPO averaged 85.25 per cent across the period, a pattern consistent with negative operating leverage in which cost growth outpaces revenue growth and compresses profit even while revenue rises.

Efficiency can equally be read from the asset side through Fixed Asset Turnover (FAT), which held near 0.91–0.92 times over 2018–2020, rose to 1.20 times in 2021 as revenue growth far exceeded fixed-asset growth, then declined to a low of 0.83 times in 2024 as fixed-asset growth outstripped revenue growth, before flattening at 0.84 times in 2025. With the sole exception of 2021, FAT remained consistently below one, indicating that each rupiah invested in fixed assets has yet to generate an equivalent rupiah of revenue.

The efficiency problem facing listed hospital issuers is therefore two-sided: a cost side reflected in BOPO consistently above 85 per cent, and an asset-utilisation side reflected in FAT largely below one. The two are interrelated, since depreciation from fixed-asset investment inflates operating expenses while those same assets have yet to generate proportionate revenue. Ratios such as BOPO and FAT, however, describe efficiency one relationship at a time and cannot capture the simultaneous interaction of multiple inputs and output in a single measure. Farrell (1957) distinguishes technical efficiency, the capacity to produce maximum output from given inputs, from allocative efficiency, the capacity to combine inputs optimally at their relative prices. Data Envelopment Analysis (DEA), developed by Charnes, Cooper, and Rhodes (1978), addresses this measurement problem as a non-parametric method that evaluates relative efficiency across multiple inputs and outputs simultaneously without requiring a predetermined production-function form, while slack analysis identifies which specific input is used in excess and Returns to Scale analysis identifies the direction of a unit's operating scale relative to its most productive scale size.

Applications of DEA in the health sector are well established but unevenly distributed. Harmadi and Irwandy (2018) reported an average technical efficiency of 0.789 among government hospitals in Indonesia; Hardiyana, Heriyanto, and Rachmatin (2014) combined DEA with principal component analysis for government hospitals in West Java and found that not all were efficient; and Devani and Suwandi (2021) found that almost all non-inpatient community health centres operated efficiently. Internationally, Alatawi, Niessen, and Khan (2020) found 75.8 per cent of public hospitals in Saudi Arabia technically inefficient, and Kamel and Mousa (2021) showed that the number of efficient isolation hospitals in Egypt during the COVID-19 pandemic rose when the assumption was relaxed from constant to variable returns to scale. These studies are dominated by public hospitals and primary care facilities and rely on operational or clinical variables such as bed numbers, patient volumes, or personnel counts. A recent systematic review of acute care hospital studies covering 1984–2022 likewise finds that labour-related inputs and hospital beds are the most frequently used inputs, while outpatient visits, surgeries, and admissions are the most frequently used outputs (Pai et al., 2024).

Research on private hospitals holding issuer status in the capital market, particularly using variables drawn from audited financial statements, remains limited. The closest evidence is a DEA study of corporate hospitals in India over financial years 2018–2021, which found that 70 per cent of the sampled hospitals were inefficient

under variable returns to scale (Mishra et al., 2024). This gap matters because listed hospital companies are accountable to shareholders and the public for the management of large asset bases, and because their investment decisions are shaped by corporate expansion and capital-market considerations rather than public-service budgeting alone. The novelty of this study therefore lies in its object of analysis—hospital companies listed on the Indonesia Stock Exchange—and in a variable specification built entirely on financial-statement items measuring the production stage in which net fixed assets, cost of revenue, and operating expenses are converted into revenue. Observing each issuer repeatedly over eight years within a single pooled frontier further allows efficiency to be examined in relation to corporate expansion, asset utilisation, and cost behaviour over time. A pooled specification is adopted, rather than a window analysis or Malmquist Productivity Index, because the study's objective is to locate where inefficiency originates across a single common frontier of 48 DMU-year observations, not to decompose period-to-period productivity change, which would require the additional sub-period frontiers and technological-change assumptions that those methods entail; this choice therefore matches method to objective rather than substituting for a productivity-change analysis. The study's theoretical contribution to the corporate finance literature in emerging markets lies in extending production-stage efficiency measurement, conventionally applied to public and primary-care providers, to capital-market-listed hospital companies whose asset and cost decisions are simultaneously disciplined by corporate governance and capital-market expectations.

Accordingly, this study pursues four objectives: to measure production-stage efficiency during 2018–2025 using an input-oriented VRS model; to identify the Returns to Scale position of each decision-making unit relative to its most productive scale size; to quantify the input slack that must be reduced for inefficient units to reach the frontier; and to examine the characteristics through which high-performing issuers achieve efficiency, viewed from both cost management and asset utilisation. The contribution lies in shifting the discussion from whether a hospital company is efficient towards where its inefficiency originates and how differences in asset utilisation, operating costs, and operating scale are reflected across listed hospital companies.

RESEARCH METHODS

Research Design and Sample

This study applies a quantitative descriptive-exploratory design to measure and map the relative efficiency of hospital issuers listed on the Indonesia Stock Exchange (IDX), using Data Envelopment Analysis (DEA), a non-parametric linear-programming technique that constructs an empirical efficiency frontier from the best practice actually attained within the sample. The population comprises the fifteen issuers in the healthcare providers sub-sector listed on the IDX during the observation period, from which six were drawn by purposive sampling using three sequential criteria: an integrated healthcare service business model (three issuers excluded, twelve retained), the characteristics of a general rather than single-specialty hospital (two excluded, ten retained), and complete financial statements for 2018–2025 with a listing date before 2018 (four excluded, six retained). The six issuers retained are PT Mitra Keluarga Karyasehat Tbk (MIKA), PT Siloam International Hospitals Tbk (SILO), PT Medikaloka Hermina Tbk (HEAL), PT Sejahteraraya Anugrahjaya Tbk (SRAJ), PT Sarana Meditama Metropolitan Tbk (SAME), and PT Royal Prima Tbk (PRIM). The period spans 2018 to 2025, producing 48 DMU-year observations. A pooled specification is used, so every

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issuer-year combination is an independent observation evaluated against one common frontier. All data are secondary, drawn from audited annual financial statements published through the IDX.

Operational Definition of Variables

The model employs three input variables and one output variable, all measured in rupiah and taken directly from the audited financial statements without further reconstruction. Net fixed assets (X_1) denote the book value of property, plant and equipment after accumulated depreciation, in line with PSAK No. 16. Cost of revenue (X_2) represents the direct costs of delivering health services and traceable to the service unit. Operating expenses (X_3) cover all operating costs outside cost of revenue, including administrative and managerial functions, non-medical staff salaries, marketing, facility maintenance, and professional fees. Revenue (Y_1) is restricted to the net revenue account in the statement of profit or loss; other income and finance income presented separately are excluded. Revenue is used as the sole output because it is the only production-stage result consistently measurable from audited financial statements across all six issuers, and because it aggregates the monetary effect of service volume, case mix, and tariff structure without requiring clinical or service-level data that issuers do not disclose uniformly; non-financial indicators such as bed occupancy and length of stay are instead used, as described in Section 5, to interpret the DEA results qualitatively rather than as model variables.

Data availability is one of the recognised approaches to selecting inputs and outputs in hospital DEA, alongside literature review, systematic methods, and expert judgement (Zubir et al., 2024). A related measurement limitation concerns net fixed assets, which under PSAK No. 16 are carried at historical cost net of accumulated depreciation and are not revalued for period-to-period medical-sector inflation; given that Indonesian medical inflation averaged 12 to 13 per cent over 2019–2023, the book value used in this study may understate the current replacement value of installed capacity, so slack measured against net fixed assets should be read as a book-value rather than a replacement-cost measure of excess capacity. The four variables therefore comprise three inputs (X_1, X_2, X_3) and one output (Y_1).

Variable Validation

Prior to DEA estimation the specification was verified through three tests. Grey Relational Analysis (GRA) detects information redundancy among the input variables: data are normalised to the interval [0,1], the grey relational coefficient is computed as in Equation (1), and the values are averaged into the grey relational grade in Equation (2), with a grade above the customary threshold of 0.90 indicating redundancy that would require one variable to be dropped.

$$\xi_i(k) = [\Delta\min + \zeta\Delta\max] / [\Delta_i(k) + \zeta\Delta\max] \quad (1)$$

$$\Gamma_i = (1/n) \Sigma_{k=1}^{n} \xi_i(k) \quad (2)$$

where $\Delta_i(k)$ is the absolute difference between the reference series $x_0(k)$ and the comparison series $x_i(k)$; $\Delta\min$ and $\Delta\max$ are the smallest and largest differences across all comparisons; ζ is the distinguishing coefficient, conventionally set at 0.5; Γ_i is the grey relational grade; and n is the number of observations.

Isotonicity testing confirms that the input–output relationship is monotonically positive, a requirement of the model, and uses the Pearson correlation coefficient in Equation (3). The coefficient of variation in Equation (4) confirms that each variable

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exhibits sufficient dispersion across DMUs for the model to discriminate meaningfully between them.

$$r_{xy} = [n\Sigma xy - (\Sigma x)(\Sigma y)] / \sqrt{\{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]\}} \quad (3)$$

$$CV = (\sigma / \mu) \times 100\% \quad (4)$$

where r_{xy} is the correlation between an input x and revenue y; σ is the standard deviation; and μ is the mean of the variable concerned.

The DEA Model

Efficiency was estimated using an input-oriented model under the Variable Returns to Scale (VRS) assumption, also known as the BCC model (Banker et al., 1984). The input orientation matches the objective of identifying how far input use can be reduced while maintaining observed revenue, and reflects the practical reality that hospital management controls resource use more than service demand, which is largely externally determined. The VRS assumption accommodates the substantial differences in operational scale among the six issuers. A recent variable-returns-to-scale application to 8,589 hospital-year observations of United States acute care hospitals adopted the same assumption because hospitals operate at very different scales (Dolezel & Sawesi, 2026) . In envelopment form the model is written as Equations (5) to (8).

$$\min \theta - \varepsilon(\Sigma_i s_i^- + \Sigma_r s_r^+) \quad (5)$$

$$\text{subject to} \quad \Sigma_j \lambda_j X_{ij} + s_i^- = \theta X_{i0} \quad (6)$$

$$\Sigma_j \lambda_j Y_{rj} - s_r^+ = Y_{r0} \quad (7)$$

$$\Sigma_j \lambda_j = 1, \quad \lambda_j \geq 0, \quad s_i^- \geq 0, \quad s_r^+ \geq 0 \quad (8)$$

where θ is the technical efficiency score of the evaluated DMU; λ_j is the intensity weight indicating the contribution of DMU j in forming the peer reference set; s_i^- and s_r^+ are input and output slack respectively; X_{i0} and Y_{r0} are the inputs and output of the evaluated DMU; and ε is a non-Archimedean infinitesimal. The constraint $\Sigma\lambda_j = 1$ is the convexity condition that distinguishes the VRS/BCC model from the CRS/CCR specification. A score of $\theta = 1$ places the DMU on the estimated frontier, whereas $\theta < 1$ indicates that proportional input reduction remains possible.

Slack and Returns to Scale Analysis

Slack analysis identifies the sources of inefficiency, with values obtained directly from the optimisation of the input-oriented BCC envelopment model. Input slack greater than zero indicates non-proportional excess use of the input concerned remaining after proportional adjustment. The Returns to Scale (RTS) condition is determined from the dual value (u_0^*) associated with the convexity constraint: the further u_0^* lies from zero, the greater the deviation of the unit's operating scale from its most productive scale size (MPSS), with negative values indicating increasing returns and positive values decreasing returns. Supporting indicators—BOPO, Fixed Asset Turnover (FAT), Bed Occupancy Rate (BOR), and Average Length of Stay (ALOS)—were used solely to interpret the findings qualitatively and were not model inputs or outputs. The Grey Relational Analysis and coefficient-of-variation tests were computed in Microsoft Excel, the Pearson correlation for isotonicity testing was computed in EViews, and DEA efficiency scores, input slack, and Returns to Scale were estimated using MaxDEA-Lite 12.

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RESULTS AND DISCUSSION

Variable Validation Results

The three validation tests confirm the suitability of the specification, with results summarised in Table 1. All GRA grades fall below the 0.90 threshold, indicating no significant information redundancy and confirming that the three inputs represent distinct dimensions of the hospital cost structure. Isotonicity testing produced positive and strong correlations with revenue for every input, satisfying the directional requirement of the model. The coefficient of variation exceeds 85 per cent for cost of revenue, operating expenses, and revenue, while net fixed assets record a lower 62 per cent—consistent with the inelastic character of an item that results from long-term investment and changes only through acquisition, disposal, or gradual depreciation, whereas revenue and expenses fluctuate with operational activity each period. Taken together, the sample is sufficiently heterogeneous for DEA to discriminate meaningfully between units.

Table 1. Results of the Variable Validation Tests

Test	Variable pair / variable	Value	Threshold	Conclusion
GRA	Cost of revenue – net fixed assets	0.60	> 0.90	Not redundant
GRA	Operating expenses – cost of revenue	0.74	> 0.90	Not redundant
GRA	Net fixed assets – operating expenses	0.66	> 0.90	Not redundant
Isotonicity	Cost of revenue – revenue	0.987	positive	Suitable
Isotonicity	Operating expenses – revenue	0.986	positive	Suitable
Isotonicity	Net fixed assets – revenue	0.860	positive	Suitable
CV	Cost of revenue	91%	adequate	Suitable
CV	Operating expenses	88%	adequate	Suitable
CV	Net fixed assets	62%	adequate	Suitable
CV	Revenue	97%	adequate	Suitable

Source: processed data

Efficiency Scores

The DEA results reveal substantial differences among the six issuers. Across all 48 observations the mean efficiency score was 0.86, indicating that the sample operated on average at approximately 86 per cent of the estimated efficient input combination relative to the pooled frontier. MIKA achieved the highest mean at 0.96, followed by SILO and PRIM at 0.94, HEAL at 0.88, SAME at 0.78, and SRAJ at 0.69. Full results are presented in Table 2.

Table 2. Operational Efficiency Scores of Hospital Issuers, 2018–2025

Issuer	2018	2019	2020	2021	2022	2023	2024	2025	Mean
MIKA	0.91	0.92	0.94	1.00	0.97	0.93	0.99	1.00	0.96
SILO	0.81	0.88	0.84	1.00	0.95	1.00	1.00	1.00	0.94
HEAL	0.82	0.86	0.90	0.99	0.75	0.83	0.94	0.98	0.88
SRAJ	0.66	0.69	0.72	0.76	0.68	0.68	0.51	0.78	0.69
SAME	0.89	0.89	0.77	0.84	0.73	0.75	0.70	0.69	0.78
PRIM	1.00	1.00	1.00	1.00	0.99	0.87	0.79	0.84	0.94
Mean	0.85	0.87	0.86	0.93	0.85	0.84	0.82	0.88	0.86

Source: processed using MaxDEA-Lite 12

Measured by the frequency of perfect efficiency, SILO and PRIM reached 1.00 four times each—SILO in 2021 and 2023–2025, PRIM in 2018–2021—followed by MIKA in 2021 and 2025. HEAL never reached the frontier, though it came within 0.01 in 2021; SAME and SRAJ likewise never reached it and, unlike HEAL, never approached it. MIKA was also the most stable, with scores confined to a 0.09 range, whereas HEAL varied across 0.24 and SRAJ combined the lowest average with the widest range of 0.27. The largest cross-sectional gap occurred in 2024, when the distance between SILO at 1.00 and SRAJ at 0.51 reached 0.49, narrowing in 2025 as SRAJ recovered.

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Efficiency Dynamics over Time

The annual pattern in Figure 1 indicates that average efficiency rose from 0.85 in 2018 to 0.88 in 2025, though the trajectory was not linear. The highest annual mean of 0.93 occurred in 2021, when MIKA, SILO, and PRIM all reached the frontier and HEAL came within 0.01 of it. That year coincided with sharp revenue expansion across the sample—27.3 per cent at MIKA, 31.9 per cent at SILO, 31.8 per cent at HEAL, 49.9 per cent at SRAJ, 55.7 per cent at SAME, and 130.4 per cent at PRIM—alongside a rise in average FAT to 1.20 times and a fall in average BOPO to 80.06 per cent, the best ratio recorded over the study period.

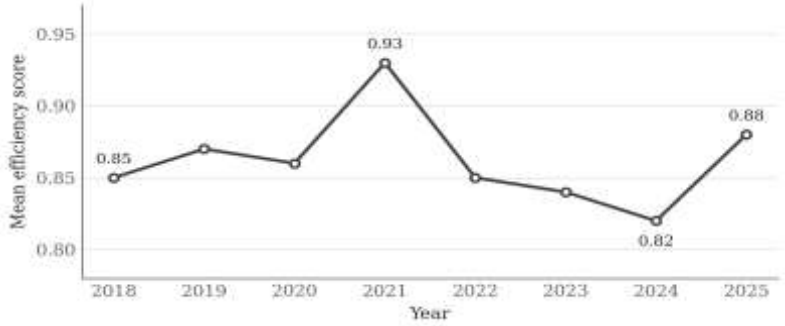


Figure 1. Annual mean efficiency score, 2018–2025

The 2021 peak is best interpreted as demand-driven efficiency. The surge in healthcare demand associated with the Delta wave of COVID-19 allowed installed capacity—beds, diagnostics, laboratory, pharmacy, and intensive care—to be used far more intensively without a proportionate increase in inputs, so the improvement reflects a higher utilisation rate of existing capacity rather than the addition of production factors. Comparable patterns are reported by Androutsou, Kokkinos, Latsou, and Geitona (2022), who found efficiency and productivity gains at hospital clinics on Rhodes, Greece, and by Ahangar et al. (2023), who documented higher bed occupancy, bed turnover, and inpatient volumes between 2018 and 2021 at hospitals affiliated with Iran University of Medical Sciences, with profitability positively associated with these utilisation indicators. A scoping review of 13 DEA studies conducted during the pandemic likewise stresses the need for dynamic and comprehensive efficiency analysis in health emergencies (Mitakos & Mpogiatzidis, 2024).

The deterioration that followed is equally informative. Average efficiency declined through 2022–2024 as fixed assets and operating commitments failed to adjust downward as quickly as revenue growth slowed—an adjustment lag consistent with the cost-stickiness mechanism of Anderson, Banker, and Janakiraman (2003), in which capacity-related costs such as wages, depreciation, and rent fall more slowly than they rise. Asymmetric cost behaviour has since been examined extensively, as a meta-analysis of studies published between 2003 and 2020 shows (Naoum et al., 2023). Sample-wide BOPO climbed to 88.68 per cent in 2022 and 94.53 per cent by 2024, while FAT stagnated between 0.83 and 0.88 times. This gradual, incomplete recovery echoes other health systems: Rhodes, Santos, and Young (2023) report that United States hospital operating margins had not fully recovered to pre-pandemic levels, and Fourlopoulou, Xenos, Messinios, and Maniadakis (2025) find that Greek public hospitals experienced declining cost productivity during the pandemic before a gradual improvement. In California, hospital utilisation had largely returned to pre-pandemic levels by 2022, yet net income margins remained below their earlier levels (Melnick & Maerki, 2023) ; in regional hospitals in Eastern Poland, efficiency fell during 2020–2021

and recovered only partially after 2022, while employment-related expenses rose from about 55 to over 73 per cent of operating costs (Małyszko et al., 2026) . A partial recovery is visible in 2025, when the annual mean rose to 0.88, driven mainly by better cost control—BOPO falling to 87.40 per cent—rather than by a rebound in asset productivity, since FAT edged up only from 0.83 to 0.84 times.

Not every hospital system responded in the same direction, which is a useful check on how far these results generalise. Sülkü, Mortaş, and Küçük (2023) found that the pandemic reduced inpatient-service efficiency at Turkish public hospitals because elective procedures were curtailed; Şahin, Göktaş, Bölükbaşı, and Şenay Ulaş (2024) reported declining technical efficiency at Turkish teaching hospitals during 2020–2021 even as total productivity rose, attributing the latter to technological change; and Wang and Xu (2024), studying private hospitals listed on the Shanghai and Shenzhen exchanges, found that the pandemic reduced profitability, liquidity, and operational efficiency. Indonesian issuers, by contrast, converted the demand surge into higher asset productivity, suggesting that pandemic-era outcomes were shaped as much by sector policy and institutional context as by internal capabilities. The overall mean of 0.86 also exceeds the 0.789 reported by Harmadi and Irwandy (2018) for Indonesian government hospitals, though the difference should not be read as a simple superiority of listed private hospitals given differences in unit of analysis and specification. It is also close to the pooled mean technical efficiency of 0.882 obtained in a meta-analysis of 37 DEA studies of hospitals in the Eastern Mediterranean Region (Ravaghi et al., 2023). Both studies nevertheless agree that full efficiency is not automatic, and that improvement depends less on general industry conditions than on how effectively each organisation manages its fundamental resources (Firian & Marjohan, 2024).

4. Returns to Scale

Beyond the efficiency score, the RTS results in Table 3 show that high technical efficiency does not necessarily mean an issuer operates at its most productive scale. MIKA remained close to that point throughout, with values confined between −0.01 and 0.04, consistent with its stable performance. SILO and HEAL moved towards increasingly negative values—SILO from near zero in 2018–2019 to −0.41 by 2025, HEAL from near zero to −0.37 over 2021–2025—indicating a deepening Increasing Returns to Scale (IRS) position even as both recorded high or perfect scores in several of those years, which suggests they were technically efficient at a scale still well below their most productive size. SRAJ and SAME instead showed positive values declining gradually towards zero, a mild Decreasing Returns to Scale (DRS) pattern easing as both approached optimal scale, while PRIM displayed the most volatile trajectory, moving from an extreme DRS position in 2018–2019 (1.00, alongside perfect efficiency) to a brief IRS episode in 2021 (−0.11) and back to moderate DRS by 2025 (0.16).

Table 3. Returns to Scale (RTS) Constant Values, 2018–2025

Issuer	2018	2019	2020	2021	2022	2023	2024	2025
MIKA	0.04	0.03	0.03	−0.01	0.02	0.02	0.02	0.02
SILO	0.03	0.02	−0.14	0.04	−0.11	−0.11	−0.16	−0.41
HEAL	0.03	0.03	0.02	−0.22	−0.32	−0.31	−0.39	−0.37
SRAJ	0.07	0.06	0.05	0.03	0.03	0.02	0.02	0.03
SAME	0.09	0.15	0.09	0.07	0.04	0.04	0.04	0.03
PRIM	1.00	1.00	0.14	−0.11	0.28	0.25	0.21	0.16

Source: processed using MaxDEA-Lite 12. Negative values indicate IRS, positive values DRS, and values approaching zero proximity to CRS.

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Input Slack

Slack analysis provides a more specific view of where inefficiency originates. Net fixed assets produced the highest frequency of slack, appearing in 26 of 48 observations (54.17 per cent), followed by operating expenses in 19 observations (39.58 per cent). Cost of revenue was the least frequent source, appearing in only three observations (6.25 per cent): SILO in 2019 and HEAL in 2024 and 2025. The distribution is presented in Figure 2, with nominal values in Tables 4 and 5.

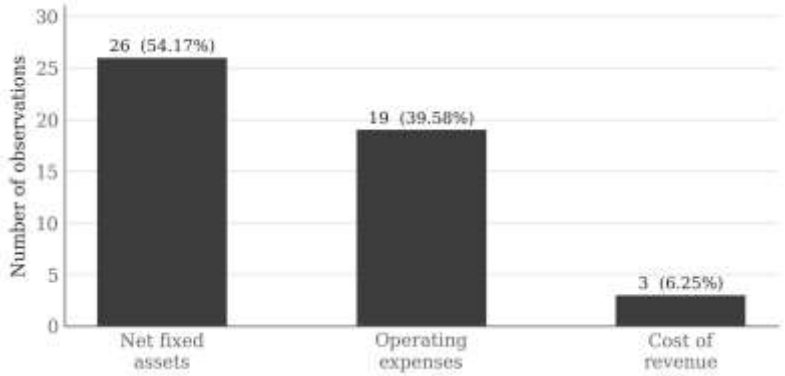


Figure 2. Frequency of input slack across 48 DMU-year observations

Table 4. Net Fixed Asset Slack by Issuer and Year (IDR billion)

Issuer	2018	2019	2020	2021	2022	2023	2024	2025
MIKA	0	0	0	0	273.48	66.42	0	0
SILO	0	0	0	0	0	0	0	0
HEAL	0	0	0	0	391.17	1,212.80	2,454.00	3,032.20
SRAJ	363.38	435.94	680.50	901.79	963.30	962.78	517.51	948.20
SAME	905.74	1,253.86	1,108.02	1,750.40	1,263.60	1,547.90	1,530.46	1,647.59
PRIM	0	0	0	0	158.60	107.20	83.14	15.54

Source: processed using MaxDEA-Lite 12

Table 5. Operating Expense Slack by Issuer and Year (IDR billion)

Issuer	2018	2019	2020	2021	2022	2023	2024	2025
MIKA	32.61	56.95	20.19	0	0	0	38.05	0
SILO	92.68	0	36.10	0	25.04	0	0	0
HEAL	227.51	257.83	190.22	28.23	0	0	0	0
SRAJ	0	0	0	0	0	0	0	156.92
SAME	1.68	63.35	38.43	4.79	0	0	0	0
PRIM	0	0	0	0	13.20	9.50	8.70	0

Source: processed using MaxDEA-Lite 12. Cost-of-revenue slack occurred in only three observations: SILO in 2019 (IDR 118.64 billion) and HEAL in 2024 and 2025 (IDR 333.51 billion and IDR 609.87 billion).

The composition of this inefficiency shifted markedly over time. During 2018–2021 operating-expense slack was the more common source, appearing in 13 of 24 observations and reflecting salaries and employee benefits, depreciation, rent, and administrative and marketing expenses—consistent with Ozcan (2014), who attributes hospital inefficiency largely to underused operational resources, particularly labour and administrative costs, and with Jacobs, Smith, and Street (2006), who emphasise management's ability to control resource use without compromising care quality. From 2022 onward the dominant source shifted decisively towards net fixed assets, and the problem also broadened: fixed-asset slack was no longer confined to SRAJ and SAME, which had struggled from the start, but began appearing at MIKA, HEAL, and PRIM. The period therefore marks a transition from an operating-cost problem to a capacity-utilisation problem. The three cost-of-revenue slacks fit this reading: at SILO in 2019 cost of revenue grew 19.4 per cent against revenue growth of 17.7 per cent, and at

HEAL in 2025 it grew 10.2 per cent against 6.2 per cent, driven mainly by medicines and medical supplies together with depreciation—items Abdulsalam and Schneller (2019) identify as among the largest hospital costs after labour.

The reason fixed assets became the more persistent constraint after 2021 lies in their relative inflexibility. Operating expenses can be adjusted at least partially through staffing, procurement, and administrative policy, even though wages and depreciation remain sticky in the short run—a mechanism formalised by Anderson, Banker, and Janakiraman (2003) and extended by Banker, Byzalov, and Chen (2013), who show that stickiness intensifies as the proportion of fixed costs grows, making efficiency more sensitive to any slowdown in revenue. Fixed assets are less flexible still: once a building or item of equipment is acquired, its depreciation and capacity commitments persist regardless of utilisation. Evidence from 101 Brazilian hospitals over 2010–2019 is consistent with this reading: a higher proportion of fixed assets in total assets was associated with more asymmetric cost behaviour, especially in private and small hospitals (Da Silva et al., 2024). Normalisation of demand after 2021 therefore exposed unused capacity far more clearly than pandemic conditions had allowed. This differs from Piubello Orsini, Leardini, Vernizzi, and Campedelli (2021), who found administrative and technical labour, rather than fixed assets, the input most in need of reduction among public hospitals in the Veneto region of Italy—underscoring that the input driving inefficiency is contingent on organisational form and cost structure.

Characteristics and Patterns of Efficiency Achievement

Synchronised expansion (MIKA, SILO).

MIKA shows the most consistent efficiency profile, with a mean of 0.96 within a narrow 0.91 to 1.00 range and only isolated, quickly resolved slack: IDR 56.95 billion in operating-expense slack in 2019, tied to a 60.4 per cent rise in sales-related wage costs, and a brief episode of fixed-asset slack in 2022–2023 as new facilities came online before being absorbed by 2024. Its measured, staged expansion kept additional assets and costs matched by revenue growth. SILO's mean of 0.94 reflects a similarly strong performance at much larger operational scale; notably, SILO recorded no net fixed-asset slack at any point during 2018–2025 even as its RTS position deepened towards IRS, indicating that each addition to its asset base was absorbed into service delivery quickly enough to avoid idle capacity.

Investment-lag pattern (HEAL).

HEAL, averaging 0.88, shows the clearest shift in the composition of its slack, from operating expenses in 2018–2021—peaking at IDR 257.83 billion in 2019, driven by a 15.3 per cent rise in wage costs and an eightfold increase in receivables-impairment provisions—to net fixed assets thereafter, reaching IDR 3,032.20 billion by 2025. Importantly, this rising fixed-asset slack is accompanied by a rising bed-occupancy rate over the same period. The distinction matters for interpretation: a temporary investment lag is defined here as fixed-asset slack that coincides with rising utilisation, indicating that newly built capacity is still being absorbed into service delivery, whereas permanent idle capacity is fixed-asset slack that persists alongside flat or declining utilisation, indicating that the capacity itself is structurally underused. HEAL's rising slack alongside rising bed occupancy places it in the former group. Cooper and Kaplan (1992) define unused capacity as the gap between the capacity of resources supplied and the capacity actually used, so that newly acquired capacity appears as slack until activity volume catches up.

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Persistent idle capacity (SRAJ, SAME).

SRAJ, with the lowest mean at 0.69, falls in the permanent idle-capacity group: it combines persistent fixed-asset slack in all eight years with utilisation indicators confirming genuine idle capacity rather than a temporary lag—bed occupancy stayed below 60 per cent throughout 2021–2025, ranging between 45.75 and 52.2 per cent, alongside a shortening average length of stay from 5.0 days in 2021 to between 3.1 and 3.8 days thereafter. Horngren, Datar, and Rajan (2012) define idle capacity as available capacity exceeding capacity actually used, which Green (2002) attributes in hospitals to buffers held in anticipation of demand surges and which Roberts et al. (1999) show erodes asset productivity because ownership costs continue to be borne when volume falls short. SAME, averaging 0.78, shows a comparably persistent pattern, reaching IDR 1,647.59 billion of fixed-asset slack in 2025, but its case is complicated by a corporate-action history: impairment losses early in the period alongside a 44.4 per cent revenue decline in 2019, followed by an acquisition that substantially enlarged its asset base through consolidation. Maile et al. (2022) note that acquisition benefits depend on the success of operational and systems integration, making SAME's idle capacity harder to attribute to underutilisation alone.

Volatile, demand-driven pattern (PRIM).

PRIM maintained perfect efficiency during 2018–2021 but declined subsequently as demand normalised, with slack appearing in operating expenses—BOPO reaching 101.38 per cent in 2023 and 106.80 per cent in 2024 while FAT fell to between 0.51 and 0.52 times—and, from 2022, in fixed assets as well; its score fell to a low of 0.79 in 2024 before recovering to 0.84 in 2025. Its efficiency is driven more by changes in service utilisation than by changes in asset structure, a characteristic linked to the large share of JKN patients in its revenue, which sustains high facility utilisation but limits flexibility in revenue per patient because tariffs are administratively set. Read together, the issuer-level evidence indicates that efficiency is associated less with the absolute size of an issuer's asset base than with whether capacity, operating costs, and revenue remain in proportion to one another—consistent with Hollingsworth (2008), who finds that hospital efficiency depends more on management's capacity to use resources optimally than on organisational scale, and with O'Neill et al. (2008) who characterise the efficient organisation in DEA terms as one that converts inputs into outputs without resource waste.

Managerial and Corporate Implications

Three priorities follow for hospital management. First, capacity expansion should be synchronised with realistic expectations of patient volume and revenue growth rather than anticipated in advance of demand, since the fixed-asset slack emerging after 2021 at several previously efficient issuers shows how quickly excess capacity appears once growth assumptions are not met. Second, existing facilities should be utilised more intensively before further fixed assets are added, particularly where DEA identifies persistent rather than transitional slack; the contrast between multi-year idle capacity at SRAJ and SAME and shorter investment-lag episodes at MIKA and HEAL shows why a single response would not fit both. Third, operating-cost control remains important in its own right, since operating-expense slack dominated the earlier years and re-emerged at SILO, PRIM, and SRAJ later, so that managing labour costs, depreciation,

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rent, and procurement in line with activity levels continues to matter even as fixed-asset utilisation becomes the more visible constraint.

The RTS evidence carries a further implication: expansion decisions cannot be evaluated from company size alone. A larger network can generate economies of scale when capacity is fully utilised—economies that the deepening IRS positions of SILO and HEAL suggest may still be available to them—but expansion can equally produce decreasing returns when additional capacity is not matched by output, as PRIM's volatile trajectory and SAME's acquisition-driven asset growth illustrate. Acquisitions and new facility development should therefore be accompanied by post-investment utilisation monitoring rather than treated as complete once construction is finished, since DEA identifies not only whether an observation is inefficient but which input should be reduced, or better utilised, to approach the frontier.

8. Limitations

Four limitations should be noted. First, the analysis covers six issuers and therefore describes relative efficiency within the selected sample rather than the efficiency of all hospitals in Indonesia. Second, the output specification is limited to revenue, capturing the financial dimension of hospital production but not clinical outcomes or quality of care. Third, and related, revenue as a single output is sensitive to differences in tariff and pricing structure across issuers: an issuer with a large share of JKN patients under the administratively fixed INA-CBGs scheme, such as PRIM, generates revenue from a different pricing regime than an issuer whose case mix leans more heavily towards privately-paid tariffs, so two issuers converting comparable volumes of service into revenue at different tariff structures need not be equally efficient in a clinical or operational sense even when their DEA scores coincide; the efficiency scores in this study should therefore be read as production-stage financial efficiency rather than a direct measure of clinical productivity. Fourth, the pooled frontier does not establish the causal determinants of efficiency. Future research may incorporate service-quality outputs, patient-level indicators, or a payer-mix control to separate tariff-structure effects from underlying operational efficiency, and may compare listed hospital companies with public or non-listed hospitals within a common framework.

CONCLUSION

This study evaluated the production-stage operational efficiency of six general hospital issuers listed on the Indonesia Stock Exchange during 2018–2025 using a pooled input-oriented VRS model. The overall mean efficiency was 0.86 across 48 observations, improving from 0.85 in 2018 to 0.88 in 2025 and peaking at 0.93 in 2021, with MIKA highest at 0.96 and SRAJ lowest at 0.69. Although no issuer was fully efficient throughout the period, performance improved gradually towards its end.

Scale positions relative to the most productive scale size were not uniform: MIKA remained close to that point, SILO and HEAL occupied increasing-returns positions, SRAJ and SAME occupied mild decreasing-returns positions moving towards constant returns, and PRIM shifted repeatedly between the two.

Net fixed assets were the dominant source of input slack at 54.17 per cent of observations, against 39.58 per cent for operating expenses and 6.25 per cent for cost of revenue, and the dominant source shifted from operating expenses during 2018–2021 to net fixed assets from 2022 onward, indicating that the central challenge evolved from

controlling operating costs towards utilising the capacity created through hospital expansion.

Issuers reaching the frontier were those able to reduce operating costs when service volume fell and to deploy additions to net fixed assets productively, whereas those that did not tended to sustain operating costs despite falling volume and to add fixed assets without commensurate revenue growth, so further asset expansion should be accompanied by a clear utilisation strategy and a realistic time horizon for revenue generation, with persistent idle capacity requiring different managerial attention from temporary investment lag.

For capital market investors, these findings carry a practical implication for evaluating hospital issuers' inorganic expansion decisions. Because conventional ratios such as BOPO and FAT describe cost and asset efficiency separately, they can understate the risk embedded in an acquisition or new-facility announcement, whereas a DEA score that incorporates net fixed assets, cost of revenue, operating expenses, and revenue simultaneously offers a more complete signal of whether an issuer's expansion has been matched by proportional revenue generation. Investors assessing acquisition-driven asset growth, such as SAME's post-acquisition consolidation, or capacity expansion undertaken during a demand upswing, such as PRIM's 2018–2021 investment, should look beyond announcement-stage narratives to post-investment utilisation evidence, since persistent input slack after an expansion is itself an indicator of unresolved integration or absorption risk.

Statement on the Use of Artificial Intelligence

AI tools were used in a limited, supporting role in the preparation of this manuscript. The authors conceived the study, collected and analysed the data, conducted the literature search, and wrote the original manuscript. Artificial intelligence tools were used only to assist with language improvement, grammar checking, and formatting for clarity and readability, and, during revision, to help check reference details (such as DOIs and publication data) and format the reference list. The tools used were Claude (Anthropic) and Grammarly. The authors selected all sources and remain fully responsible for the accuracy, originality, integrity, and academic content of the manuscript. All AI-assisted content was reviewed and verified by the authors before submission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Conceptualization, methodology, analysis, and writing—original draft, E.N.L.; supervision and writing—review and editing, M.M. and Z. All authors have read and approved the final manuscript.

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