

Efficiency and productivity of Mongolian public hospitals: a three-stage DEA and Malmquist productivity index approach

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CITATION

Bolorchimeg Uranchimeg, Young Kyun Kim. Efficiency productivity of Mongolian public hospitals: a three-Stage DEA and Malmquist productivity index approach. International Journal of Social Science and Humanities Research-MIYR, 2026, 6(3), 58~77.

<https://doi.org/10.53468/mifyr.2026.6.3.58>

ARTICLE INFO

Received: 29 August 2026

Revised: 01 September 2026

Accepted: 21 September 2026

Available online: 30 September 2026

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Abstract - This study evaluates the efficiency and productivity of 31 Mongolian public hospitals over the period 2017–2022 using an integrated three-stage Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and Malmquist Productivity Index (MPI) framework. An input-oriented VRS/BCC model was employed using hospital beds, physicians, nurses, other staff, and expenditure as inputs, with total patients and revenue as outputs. In Stage 2, SFA was applied to input slacks to account for socioeconomic, demographic, geographic, and COVID-19-related operating conditions before efficiency was re-estimated using adjusted inputs in Stage 3. The results show that environmental adjustment materially changed hospital efficiency estimates. Mean pure technical efficiency was higher in Stage 3 than in Stage 1 in every year, and the difference was statistically significant ($z = -11.064$, $p < .001$). The SFA results further indicate that hospital resource utilization was associated with heterogeneous operating conditions, including regional socioeconomic characteristics, population structure, geographic accessibility, and pandemic-related workforce changes. The Malmquist analysis showed that productivity declined slightly in 2017–2018 (MEPI = 0.9673) but improved in all subsequent periods, reaching its highest level in 2020–2021 (MEPI = 1.5771). During this period, technological change contributed more strongly to productivity growth than efficiency catch-up. Overall, the findings demonstrate that hospital performance in Mongolia reflects both managerial efficiency and external operating conditions. By incorporating financial resources together with physical and human inputs, this study provides a broader resource-allocation perspective and offers evidence for environment-adjusted benchmarking, more equitable performance evaluation, and more efficient allocation of public healthcare resources.

Keywords: Three-stage DEA; Stochastic frontier analysis; Malmquist productivity index; Public hospital efficiency; Environmental adjustment; Financial resource allocation

1. INTRODUCTION

Improving the efficiency and productivity of healthcare delivery is an important policy issue in systems constrained by limited public finance, workforce availability, and geographic accessibility. This challenge is particularly relevant in Mongolia, where a vast territory and dispersed population require public hospitals to maintain essential service capacity under highly heterogeneous regional conditions. Efficient allocation of beds, healthcare personnel, and financial resources is therefore important not only for controlling public expenditure but also for maintaining equitable access to healthcare. This concern is also consistent with recent Mongolian research linking economic growth with the design of sustainable economic policy [1]. Data Envelopment Analysis (DEA) is widely used to evaluate relative efficiency because it accommodates multiple inputs and outputs without requiring a predetermined production function. The CCR model established the original

constant-returns-to-scale framework [2], while the BCC model introduced variable returns to scale, enabling pure technical and scale efficiency to be distinguished [3]. DEA has since been extensively applied to hospital performance analysis [4], including studies of Korean public and private hospitals [5–7].

However, conventional DEA treats deviations from the efficiency frontier as inefficiency and cannot explicitly distinguish managerial performance from environmental effects or statistical noise. Stochastic frontier analysis provides a statistical framework for separating inefficiency from random disturbance [8,9]. Building on this principle, Fried et al. developed the three-stage DEA approach, in which input slacks are modeled against environmental conditions before adjusted inputs are used to re-estimate efficiency [10]. Hospital applications have shown that such adjustment can materially change efficiency estimates. Chen et al., for example, found that mean efficiency among Chinese regional public hospitals increased from 0.927 to 0.981 after environmental adjustment [11]. Similar multistage approaches have demonstrated that institutional and regional conditions can substantially affect measured hospital performance [12–14].

Another important issue is variable selection. Hospital DEA studies commonly employ beds and healthcare personnel, yet input-output specifications vary substantially across studies [15]. A systematic review confirmed that no single variable specification is universally appropriate for all hospital settings and emphasized the importance of matching variables to the study objective and institutional context [15]. This is particularly relevant for publicly financed hospitals because physical resources alone may not fully capture the economic resources used to provide healthcare services.

Accordingly, this study incorporates hospital expenditure as a financial input and hospital revenue as an output, together with beds and healthcare personnel. This specification extends efficiency analysis from a purely technical perspective toward a broader resource-allocation perspective. Previous hospital productivity research has similarly incorporated financial and operational inputs to assess how limited healthcare resources are transformed into service outputs [16]. In the Mongolian context, this economic dimension is especially relevant because public hospitals operate under budgetary constraints while simultaneously maintaining minimum service capacity across geographically diverse regions.

Static DEA also cannot identify whether changes in performance over time result from efficiency catch-up or shifts in the production frontier. The Malmquist Productivity Index addresses this limitation by measuring intertemporal productivity change [17] and decomposing it into efficiency change and technological change [18]. This distinction allows productivity improvement to be interpreted as either movement toward the existing frontier or a shift in best-practice production possibilities.

These methodological issues became particularly important during the COVID-19 period. Pandemic-related changes in patient flows, workforce availability, and hospital operations may alter measured efficiency even when formal staffing and capacity remain unchanged. Studies from Türkiye and South Korea documented substantial reductions in hospital utilization during the pandemic, demonstrating that observed efficiency changes may partly reflect external service disruptions rather than managerial performance alone [19,20].

Despite the broad international use of DEA, three gaps remain relevant to Mongolia. First, hospital-level efficiency has rarely been evaluated while explicitly separating managerial inefficiency from environmental heterogeneity and statistical noise. Second, financial resource use is not consistently incorporated alongside physical and human resources, limiting the economic interpretation of efficiency. Third, static efficiency measures alone do not reveal whether productivity changes originate from efficiency catch-up or technological/frontier shifts. Previous stochastic and DEA-based studies of hospital efficiency further indicate that managerial performance should be interpreted together with institutional and operating conditions [21].

To address these gaps, this study applies an integrated three-stage DEA–SFA–Malmquist Productivity Index framework to a balanced panel of 31 Mongolian public hospitals from 2017 to 2022. It first estimates hospital efficiency using an input-oriented VRS/BCC framework, then evaluates the association between external operating conditions and input slacks before re-estimating efficiency with adjusted inputs. Finally, the Malmquist index is used to examine productivity change over time.

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The contribution of this study lies in integrating environmental adjustment, financial resource use, and longitudinal productivity analysis at the individual public-hospital level in Mongolia. This framework provides a more context-sensitive basis for hospital benchmarking and for assessing how limited public healthcare resources are transformed into services.

The study addresses the following research questions:

1. How do hospital efficiency scores change after adjustment for environmental factors and statistical noise?
2. Which external operating conditions are significantly associated with hospital input slacks?
3. How does incorporating financial resources alongside physical and human resources contribute to hospital efficiency assessment?
4. How did hospital productivity change from 2017 to 2022, and was this change associated primarily with efficiency catch-up or shifts in the production frontier?
5. What implications do the findings have for hospital benchmarking and public resource allocation in Mongolia?

The findings are intended to provide a more context-sensitive basis for evaluating public hospital performance and to support future policy development in hospital benchmarking and health-resource allocation.

2. RESEARCH METHODS

2.1 Research Design

This study applies an integrated three-stage DEA–SFA–MPI analytical framework to 31 Mongolian public hospitals to examine changes in efficiency and productivity over the period 2017–2022. The overall research model is presented in Figure 1. This framework provides a comprehensive analytical approach that distinguishes managerial inefficiency from the effects of exogenous environmental factors while simultaneously assessing longitudinal changes in hospital productivity. For data preparation, statistical analysis, model estimation, and result validation, Stata 18, MaxDEA, and Visual Studio were employed. These software tools were used to process and organize the panel dataset, estimate the DEA and SFA models, calculate efficiency and productivity indicators, and generate the final analytical results.

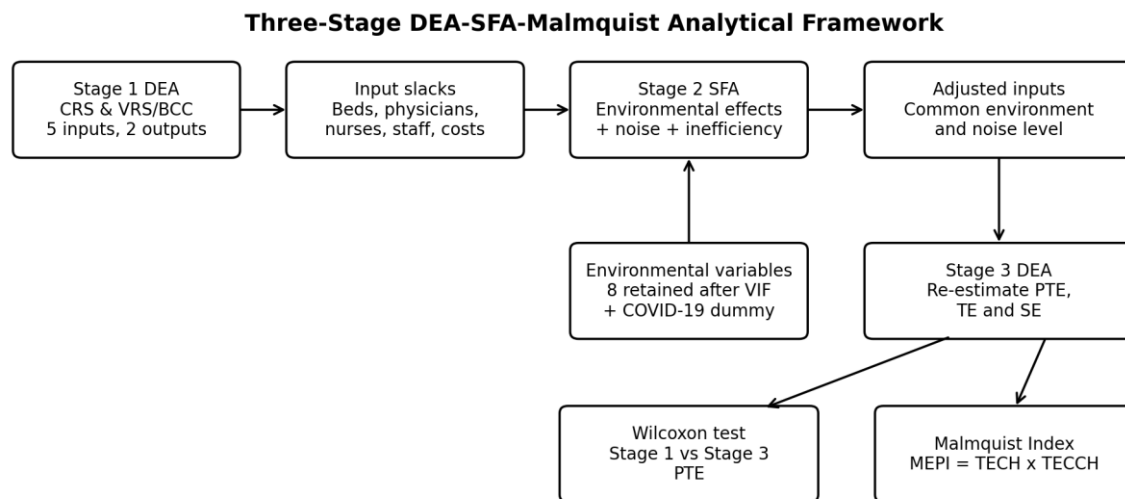


Figure 1. Research Framework

2.2 Data Envelopment Analysis (DEA)

Following established DEA and three-stage efficiency methods [10,22], an input-oriented Slacks-Based Measure (SBM) model was applied.

The SBM efficiency score is defined as:

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s} \sum_{r=1}^s \frac{s_r^+}{y_{r0}}}$$

subject to: $x_0 = X\lambda + s^-, y_0 = Y\lambda - s^+, \lambda \geq 0, s^- \geq 0, s^+ \geq 0$

- ρ^* : efficiency score
- x_0, y_0 : input and output vectors of the reference DMU
- X, Y : input and output matrices of all DMUs
- s^- : input slack vector
- s^+ : output slack vector
- λ : weight vector
- m, s : number of inputs and outputs, respectively

2.3 Stochastic Frontier Analysis (SFA)

Building on stochastic frontier models [8,9], the input inefficiency (slack) estimated in the DEA stage was regressed on exogenous environmental variables, thereby separating managerial factors from environmental factors.

The SFA regression model takes the form:

$$S_{ni} = f(Z_n; \beta) + v_{ni} + u_{ni}$$

- S_{ni} : input slack of the n -th DMU for the i -th input
- β : regression coefficient vector for environmental variables
- v_{ni} : random noise (statistical noise)
- u_{ni} : management inefficiency term
- Z_n : environmental variables

2.4 Adjusted DEA Re-estimation (Stage 3)

To remove the statistical and environmental components estimated by SFA, input values were adjusted as follows:

The adjusted input values are computed as:

$$\hat{x}_{ni} = x_{ni} + \left[\max_n (\hat{f}(Z_n; \hat{\beta})) - \hat{f}(Z_n; \hat{\beta}) \right] + \left[\max_n (\hat{v}_{ni}) - \hat{v}_{ni} \right]$$

- $\hat{x}_{ni}$: adjusted input value with environmental and noise components removed
- x_{ni} : original observed input value

Using the random noise and inefficiency terms estimated by SFA, DEA was re-estimated to yield pure technical efficiency (PTE) scores.

2.5 Malmquist Productivity Index (MPI)

Following the established Malmquist productivity framework [17,18], productivity change was measured using the Malmquist Productivity Index:

The MPI is decomposed as:

$$MPI = EFFCH \times TECHCH$$

$$MPI^{t,t+1} = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \right]^{1/2}$$

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- EFFCH (TECH in this paper): efficiency change (technical efficiency change)
- TECHCH (TECCH in this paper): technical change (frontier shift)

Values greater than 1 indicate productivity improvement; values less than 1 indicate regression.

2.6 Variable Selection

To define the input, output, and environmental variables for DEA analysis, prior quantitative and bibliometric studies targeting Mongolian public hospitals were synthesized. On this basis, input variables, output variables, and 11 exogenous environmental variables appropriate to the study context were selected. The variable definitions and data sources are presented in Table 1.

Table 1. Variable Selection Rationale and Data Sources

Category	Variable Name	Description	Key References	Data Source
Input variables	Number of Beds (<i>Beds</i>)	Fundamental resource variable representing hospital capacity	[6,15]	Ministry of Health of Mongolia, 2017–2022
	Number of Physicians (<i>Doctors</i>)	Key indicator of clinical capacity, reflecting the scale of specialist medical staff	[15,21]	Ministry of Health of Mongolia; National Statistics Office, 2017–2022
	Number of Nurses (<i>Nurses</i>)	Personnel variable with direct influence on patient care quality and treatment outcomes	[15,23]	Ministry of Health of Mongolia; National Statistics Office, 2017–2022
	Administrative and Support Staff (<i>Other Staff</i>)	Non-clinical personnel including administrative, technical, and service staff	[15]	Ministry of Health of Mongolia; regional hospital annual reports
	Hospital Operating Costs (<i>Operating Cost</i>)	Total annual operating expenditure including personnel costs	[23–25]	Ministry of Finance of Mongolia; Ministry of Health financial statistics, 2017–2022
Output variables	Annual Patient Volume (<i>Patients</i>)	Total annual number of outpatient and inpatient visits	[13,15]	Ministry of Health of Mongolia integrated health statistics, 2017–2022
	Total Hospital Revenue (<i>Revenue</i>)	Total annual income derived from clinical and other medical services	[6,15]	Ministry of Health of Mongolia; National Statistics Office financial statistics
Environmental variables	Urbanization Rate (<i>urban</i>)	Social variable explaining the urban–rural distribution of medical resources	[15,23]	Mongolian National Statistics Office urbanization statistics
	Regional GDP (<i>gdp</i>)	Indicator of regional economic level; affects access to medical resources	[24,25]	Mongolian National Statistics Office; IMF database
	Land Area (<i>land_area</i>)	Geographic size of the region; influences hospital distribution	[25]	Mongolian National Statistics Office GIS data
	Population (<i>pop</i>)	Total regional population size	[5,15]	Mongolian National Statistics Office population census
	Mortality Rate (<i>dead_rate</i>)	Indirect indicator of regional health status and healthcare service quality	Researcher-constructed variable	WHO Global Health Statistics
	Population Density (<i>pop_density</i>)	Level of population concentration affecting healthcare accessibility and hospital utilization	Fang et al. (2024); Kim et al. (2024)	Mongolian National Statistics Office demographic statistics
	Human Development Index (<i>HDI</i>)	Composite socioeconomic indicator correlated with health outcomes	Researcher-constructed variable	UNDP Human Development Database
	Unemployment Rate (<i>unemployed</i>)	Proxy variable for regional economic conditions and household capacity to	[24,25]	Mongolian National Statistics Office labor

		afford healthcare expenditure		statistics
	Distance to Capital (<i>distance_km</i>)	Distance to Ulaanbaatar in km, serving as a proxy for healthcare accessibility	Researcher- constructed variable	Google Maps; Ministry of Health of Mongolia GIS data
	Population Aged 65 and Over (<i>pop_over65</i>)	Variable explaining increased healthcare demand associated with population aging	[15,23]	Mongolian National Statistics Office population structure statistics
	COVID-19 Pandemic (<i>covid</i>)	Dummy variable representing the exogenous operational shock of the COVID-19 pandemic. Equals 1 for 2020–2021 and 0 otherwise. A broader 2020–2022 definition is examined in robustness analysis.	[26]	Researcher-constructed dummy based on WHO Mongolia and Ministry of Health of Mongolia COVID-19 reports

2.6.1 Descriptive Statistics for Input and Output Variables

From 2017 to 2022, Mongolian public hospitals expanded in capacity and operating costs, while patient volumes declined and workforce growth remained limited. This indicates a mismatch between resource inputs and service outputs, suggesting increasing efficiency and financial sustainability pressures. Detailed statistics are reported in Table 2.

Table 2. Descriptive Statistics of Input and Output Variables (2017–2022)

Variable	Statistic	2017	2018	2019	2020	2021	2022
Number of Beds (<i>beds</i>)	Mean	260.10	269.77	276.35	278.71	324.32	379.23
	Maximum	493	494	623	623	850	877
	Minimum	100	100	100	100	100	167
	SD	91.65	99.92	112.20	109.32	142.46	179.98
Number of Physicians (<i>doctors</i>)	Mean	72.90	75.97	78.81	80.55	81.52	85.39
	Maximum	115	117	123	120	120	136
	Minimum	20	20	24	36	38	41
	SD	23.91	23.79	24.27	22.18	21.34	24.28
Number of Nurses (<i>nurses</i>)	Mean	107.35	109.87	112.19	105.26	88.52	107.90
	Maximum	205	207	231	224	168	238
	Minimum	39	44	40	33	37	34
	SD	40.10	39.42	42.46	35.59	27.92	40.51
Support Staff (<i>staffs</i>)	Mean	107.58	136.52	136.03	136.42	139.94	141.58
	Maximum	220	234	211	207	208	206
	Minimum	28	52	52	67	75	70
	SD	42.09	41.89	37.63	34.47	34.37	35.95
Operating Costs (<i>costs</i>, <i>MNT '000</i>)	Mean	192,857.90	208,753.30	300,826.60	361,736.20	543,558.80	623,231.10
	Maximum	450,232.10	480,645.60	741,056.00	825,261.40	1,268,460.00	1,556,843.00
	Minimum	28,017.19	26,871.37	28,775.20	50,092.89	89,075.79	124,391.30
	SD	131,028.80	140,316.20	209,721.40	251,990.00	377,271.10	425,116.80
Annual Patient	Mean	11,982.65	9,528.87	9,739.48	8,518.94	9,488.61	10,193.58
	Maximum	104,569	22,574	23,844	20,421	19,189	20,213

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Volume (patients)	Minimum	3,581	3,845	3,732	3,121	4,272	4,116
	SD	17,570.53	4,535.86	4,738.68	3,868.57	3,496.48	4,219.32
Total Hospital Revenue (revenues, MNT '000)	Mean	220,786.30	203,780.00	293,260.90	345,742.90	550,394.40	596,622.00
	Maximum	946,527.10	480,232.10	735,873.70	792,426.50	1,268,460.00	1,366,070.00
	Minimum	28,025.19	26,871.55	28,775.20	50,092.89	89,073.79	124,491.30
	SD	187,309.90	140,493.70	209,781.60	243,249.50	382,674.80	399,633.60

SD: Standard Deviation. Operating costs and revenues expressed in thousands of Mongolian tugrug(MNT)

2.6.2 Descriptive Statistics for Environmental Variables

Between 2017 and 2022, regional GDP, the Human Development Index (HDI), and the population aged 65 years and over increased steadily, indicating that economic development occurred alongside population aging and potentially contributed to rising healthcare demand and fiscal pressure. To capture the external effects of the COVID-19 pandemic on hospital operations, resource utilization, and financial performance, a COVID dummy variable was coded as 0 for 2017–2019 and 1 for 2020–2022. Given that annual hospital budgets are generally planned and approved in the preceding fiscal period, the 2020–2022 interval was defined as the pandemic-affected period to reflect both the immediate operational disruptions and the potential lagged fiscal effects of COVID-19. Descriptive statistics are presented in Table 3.

Table 3. Descriptive Statistics of Exogenous Environmental Variables (2017–2022)

Variable	Statistic	2017	2018	2019	2020	2021	2022
Urbanization Rate (urban)	Mean	0.32	0.32	0.32	0.32	0.32	0.32
	Maximum	1	1	1	1	1	1
	Minimum	0	0	0	0	0	0
	SD	0.48	0.48	0.48	0.48	0.48	0.48
Regional GDP (gdp, MNT billion)	Mean	8,144.43	9,179.81	10,518.59	10,444.05	11,925.92	14,619.39
	Maximum	17,030.90	18,333.10	20,297.30	17,942.10	29,546.40	39,223.30
	Minimum	3,341.30	3,721.50	4,098.60	4,478.80	3,903.90	6,027.10
	SD	4,347.10	5,010.73	5,600.60	4,852.39	6,143.87	8,335.90
Land Area (land_area, 000 km ²)	Mean	50.53	50.53	50.53	50.53	50.53	50.53
	Maximum	165.40	165.40	165.40	165.40	165.40	165.40
	Minimum	0.14	0.14	0.14	0.14	0.14	0.14
	SD	49.66	49.66	49.66	49.66	49.66	49.66
Population (pop)	Mean	111,444.50	113,320.10	114,540.70	115,970.80	117,792.20	119,491.30
	Maximum	336,932	343,619	361,689	367,679	383,892	408,797
	Minimum	4,100	4,399	4,123	4,463	4,459	4,416
	SD	84,564.85	85,127.78	87,812.88	90,099.96	93,095.61	97,109.35
Mortality Rate (dead_rate, per 100,000)	Mean	618.55	629.52	648.32	606.10	743.71	683.10
	Maximum	1,818	1,651	1,695	1,749	2,199	1,954
	Minimum	25	37	24	35	23	25
	SD	444.07	418.32	435.94	428.63	563.66	495.78
Population Density (pop_density, persons/km ²)	Mean	0.86	0.89	0.89	0.90	0.90	0.90
	Maximum	2.70	2.70	2.70	2.70	2.60	2.60
	Minimum	0.03	0.03	0.03	0.03	0.03	0.03
	SD	0.66	0.67	0.67	0.67	0.67	0.66
Human Development	Mean	0.7079	0.7130	0.7240	0.7316	0.7321	0.7351

Index (hdi)	Maximum	0.819	0.810	0.818	0.822	0.825	0.830
	Minimum	0.620	0.623	0.635	0.644	0.640	0.651
	SD	0.0651	0.0683	0.0712	0.0598	0.0630	0.0654
Unemployment Rate (unemployed, %)	Mean	8.76	8.38	9.58	7.24	8.13	6.99
	Maximum	23.50	19.60	28.60	21.40	24.50	12.30
	Minimum	2.10	2.60	2.10	1.20	2.00	0.70
	SD	4.81	3.66	5.32	3.81	5.23	2.97
Distance to Capital (distance_km, km)	Mean	445.85	445.85	445.85	445.85	445.85	445.85
	Maximum	1,709	1,709	1,709	1,709	1,709	1,709
	Minimum	7	7	7	7	7	7
	SD	465.61	465.61	465.61	465.61	465.61	465.61
Population Aged 65+ (pop_over65)	Mean	4,054.74	4,230.16	4,793.16	5,065.71	5,356.03	5,738.16
	Maximum	11,804	12,407	13,646	14,585	15,806	17,784
	Minimum	185	7	213	235	245	265
	SD	2,851.74	3,155.81	3,490.41	3,730.58	3,986.40	4,351.33
COVID-19 Pandemic (covid)	Mean	0	0	0	1	1	1
	Maximum	0	0	0	1	1	1
	Minimum	0	0	0	1	1	1
	SD	0	0	0	0	0	0

Applying the analytical framework described above, the efficiency of Mongolian public hospitals was empirically measured. The key findings are presented in the following section.

3. RESULTS

3.1 Stage-1 DEA Efficiency Results

The six-year mean efficiency scores of the 31 Mongolian public hospitals fluctuated in the range of 0.5–0.9, suggesting that further investigation is warranted to determine whether the observed inefficiency originates from within-hospital managerial capacity constraints or is more substantially influenced by organizational-structural limitations and exogenous environmental factors.

3.1.1 Pure Technical Efficiency (PTE)

The number of hospitals achieving high efficiency ($PTE \geq 0.8$) decreased from 8 in 2017 to 6 in 2022, while low-efficiency hospitals ($PTE < 0.6$) consistently accounted for a high proportion throughout the entire study period. These results suggest that technical inefficiency is not a product of transient operational failures but is rather perpetuated by structural factors such as institutional and environmental constraints and scale mismatches. Efficiency analysis results are presented in Table 4.

3.1.2 Technical Efficiency (TE)

The majority of hospitals fall in the below-0.6 range, and after 2018 no hospital achieved a TE score of 0.8 or above. This demonstrates that when scale factors are accounted for, overall efficiency levels decline substantially, indicating that scale inefficiency is a primary driver of overall efficiency deterioration. Efficiency analysis results are presented in Table 4.

3.1.3 Scale Efficiency (SE)

Overall, no more than two hospitals achieved high scale efficiency ($SE \geq 0.8$) during the entire study period, indicating that high scale efficiency was very limited. Conversely, the number of hospitals in the 0.60–0.79 range increased modestly beginning from 2021 (3 hospitals) and 2022 (2 hospitals), confirming the potential for efficiency improvement if scale adjustments are made. Some hospitals thus appear to be evaluated as inefficient not due to insufficient operational capacity per se, but rather due to operating below the optimal scale. Certain hospitals did record VRS scores of 0.8 or above, confirming that operational capacity itself is partially secured. To determine whether this inefficiency originates from internal operational limitations or from external environmental factors and structural constraints, Stage-2 SFA analysis was additionally conducted.

Table 4. Stage-1 DEA Efficiency Analysis Results

Indicator	Statistic	2017	2018	2019	2020	2021	2022
Pure Technical Efficiency (PTE)¹	Mean	0.663	0.632	0.598	0.579	0.642	0.611
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000
	Minimum	0.359	0.342	0.333	0.359	0.408	0.340
	SD	0.211	0.203	0.192	0.168	0.181	0.206
	No. hospitals ≥ 0.8	8	6	5	4	8	6
	No. hospitals 0.6–0.79	8	7	5	7	6	6
	No. hospitals < 0.6	15	18	21	20	17	19
Technical Efficiency (TE)²	Mean	0.234	0.174	0.195	0.194	0.265	0.257
	Maximum	1.000	0.309	0.313	0.278	0.432	0.489
	Minimum	0.098	0.098	0.103	0.093	0.102	0.116
	SD	0.211	0.051	0.054	0.055	0.101	0.091
	No. hospitals ≥ 0.8	2	0	0	0	0	0
	No. hospitals 0.6–0.79	0	0	0	0	0	0
	No. hospitals < 0.6	29	31	31	31	31	31
Scale Efficiency (SE)³	Mean	0.347	0.294	0.351	0.363	0.420	0.434
	Maximum	1.000	0.502	0.634	0.643	0.709	0.690
	Minimum	0.101	0.098	0.111	0.096	0.141	0.155
	SD	0.198	0.098	0.126	0.145	0.149	0.130
	No. hospitals ≥ 0.8	2	0	0	0	0	0
	No. hospitals 0.6–0.79	0	0	1	1	3	2
	No. hospitals < 0.6	29	31	30	30	28	29

¹ Pure Technical Efficiency (PTE) = VRS efficiency score

² Technical Efficiency (TE) = CRS efficiency score

³ Scale Efficiency (SE) = CRS/VRS

3.2 Stage-2 SFA-Based Efficiency Adjustment Results

Stage 2 SFA was conducted using five input slacks—beds, doctors, nurses, other staff, and costs—as dependent variables to separate environmental effects and statistical noise from managerial inefficiency. The initial specification included 11 environmental variables. Multicollinearity diagnostics identified strong correlations among population, mortality rate, population aged 65 years and over, HDI, urban status, and GDP. Because several VIF values exceeded 10, mortality rate, HDI, and population were excluded from the final specification. This reduced the mean VIF to 2.11, indicating no serious multicollinearity. Analysis results are presented in Table 5.

Table 5. Multicollinearity Diagnostics for Environmental Variables

Environmental variables	VIF1	VIF2
pop	35.231	-
dead rate	28.213	-
hdi	17.256	-
pop over65	8.994	4.293
urban	6.956	2.663
gdp	5.857	2.355
land area	3.128	2.088
distance km	2.513	1.563
pop density	1.861	1.455
COVID dummy	1.388	1.273
unemployed	1.334	1.211
Mean VIF	10.248	2.113

The final time-varying decay stochastic cost frontier model included eight environmental variables: urban status, GDP, land area, population, population density, unemployment, distance, and the COVID-19 dummy. The effects varied across input categories. Nurse slack showed the strongest sensitivity to environmental conditions, with significant associations observed for urban status, GDP, land area, population, population density, unemployment, distance, and the COVID-19 period. Doctor slack was significantly associated with population and distance, whereas other-staff slack was significantly related to GDP, land area, and the COVID-19 period. Cost slack was significantly associated with GDP and land area, while environmental effects on bed slack were comparatively weak. SFA Regression Results are presented in Table 6.

These findings indicate that the input slacks identified in Stage 1 reflect not only internal managerial inefficiency but also, to some extent, the influence of external operating conditions and random statistical disturbances. Accordingly, based on the Stage 2 SFA estimates, the original input variables were adjusted for environmental heterogeneity and stochastic effects, thereby enabling a more comparable assessment of hospitals under standardized operating conditions.

Table 6. Stage-2 SFA Regression Results

Variable	Bed Slack	Physician Slack	Nurse Slack	Other Staff Slack	Cost Slack
Urban	8.5547	2.0108	-6.9831***	5.5741	-34.5567
	(7.0043)	(2.0319)	(2.7107)	(5.5170)	(23.5133)
GDP	-0.0003	-0.0001	-0.0002	-0.0006**	-0.0018
	(0.0004)	(0.0001)	(0.0002)	(0.0003)	(0.0014)
Land area	0.0781	-0.0048	-0.0655***	0.0485	0.0384
	(0.0528)	(0.0160)	(0.0205)	(0.0429)	(0.1793)
Population density	2.4361	-0.9564	-3.1409***	4.2877	-3.3314
	(3.0203)	(0.8947)	(1.1790)	(3.1022)	(10.8377)

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Unemployment	0.7733*	−0.0544	0.0830	0.0234	3.5858***
	(0.4001)	(0.1013)	(0.1575)	(0.2745)	(1.0986)
Distance to capital	0.0051	0.0017	0.0081***	0.0033	−0.0172
	(0.0050)	(0.0017)	(0.0020)	(0.0050)	(0.0179)
Population aged 65+	0.0001	0.0004*	0.0007***	−0.0005	0.0004
	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0017)
COVID-19 dummy	5.4579	0.0989	−5.4562***	5.8845**	6.5508
	(3.5129)	(1.0258)	(1.4135)	(2.7106)	(10.4811)
Observations	186	186	186	186	186
Log likelihood	−856.768	−576.178	−658.488	−753.258	−1030.030

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Following this adjustment, Stage 3 DEA was conducted using the refined input data. This procedure helped isolate the influence of external environmental factors and random disturbances as far as possible, allowing hospital efficiency to be evaluated under conditions more closely associated with managerial performance. The results of the Stage 3 DEA are presented in the following section.

As a sensitivity analysis, the Stage 2 SFA models were re-estimated using a time-invariant (TI) specification and compared with the primary time-varying decay (TVD) model. Although some coefficients varied in magnitude, significance, and direction, the TVD specification was retained because it allows hospital inefficiency to change over time. The full TI estimation results are reported in Appendix Table A1.

3.3 Stage-3 Re-estimated DEA.

Following the adjustment of input variables based on the Stage 2 SFA estimates, DEA was re-estimated using the adjusted inputs. The Stage 3 results show noticeable changes in pure technical efficiency (PTE), technical efficiency (TE), and scale efficiency (SE) over the 2017–2022 period.

Mean PTE was 0.770 in 2017 and 0.760 in 2018, before declining to 0.674 in 2019 and 0.667 in 2020. It subsequently increased to 0.788 in 2021 and remained relatively high at 0.749 in 2022. The number of hospitals with PTE scores of 0.8 or above was highest in 2018, with 15 hospitals, followed by 13 hospitals in both 2017 and 2021. By contrast, only four hospitals reached this threshold in 2020. These results indicate considerable variation in managerial and operational performance across hospitals and years.

Mean TE increased overall from 0.257 in 2017 to 0.367 in 2022, despite a temporary decline to 0.203 in 2018. TE remained relatively low during 2018–2020 but increased markedly in 2021 and 2022, reaching 0.357 and 0.367, respectively. Nevertheless, most hospitals continued to record TE scores below 0.6 throughout the study period, indicating that overall technical efficiency remained limited for a substantial proportion of the sample.

SE also showed a general upward tendency. The mean SE was 0.339 in 2017 and declined to 0.294 in 2018, but subsequently increased to 0.357 in 2019, 0.377 in 2020, 0.435 in 2021, and 0.485 in 2022. The number of hospitals with SE scores between 0.6 and 0.79 increased particularly in the later years, reaching nine hospitals in 2022. This pattern suggests that scale-related performance improved over time, although substantial heterogeneity across hospitals remained.

Overall, the Stage 3 results indicate that efficiency patterns differed considerably across the three dimensions of efficiency. PTE remained comparatively higher than TE and SE throughout the study period, while TE and SE exhibited stronger improvement toward the end of the observation period. The detailed Stage 3 DEA results are presented in Table 7.

Table 7. Stage-3 Re-estimated DEA Efficiency Results

Indicator	Statistic	2017	2018	2019	2020	2021	2022
Pure Technical Efficiency (PTE)¹	Mean	0.770	0.760	0.674	0.667	0.788	0.749
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000
	Minimum	0.447	0.424	0.428	0.455	0.576	0.503
	SD	0.164	0.183	0.150	0.121	0.143	0.153
	No. hospitals ≥ 0.8	13	15	5	4	13	10
	No. hospitals 0.6–0.79	13	10	16	18	17	17
	No. hospitals < 0.6	5	6	10	9	1	4
Technical Efficiency (TE)²	Mean	0.257	0.203	0.228	0.239	0.357	0.367
	Maximum	1.000	0.294	0.364	0.367	1.000	1.000
	Minimum	0.081	0.080	0.082	0.078	0.090	0.125
	SD	0.206	0.056	0.074	0.092	0.224	0.183
	No. hospitals ≥ 0.8	2	0	0	0	2	1
	No. hospitals 0.6–0.79	0	0	0	0	2	1
	No. hospitals < 0.6	29	31	31	31	27	29
Scale Efficiency (SE)³	Mean	0.339	0.294	0.357	0.377	0.435	0.485
	Maximum	1.000	0.587	0.720	0.683	1.000	1.000
	Minimum	0.084	0.080	0.102	0.089	0.097	0.134
	SD	0.211	0.131	0.153	0.174	0.222	0.196
	No. hospitals ≥ 0.8	2	0	0	0	2	1
	No. hospitals 0.6–0.79	0	0	2	4	4	9
	No. hospitals < 0.6	29	31	29	27	25	21

¹ Pure Technical Efficiency (PTE) = VRS efficiency score

² Technical Efficiency (TE) = CRS efficiency score

³ Scale Efficiency (SE) = CRS/VRS

3.3.1 Comparison of Efficiency Scores: Stage 1 vs. Stage 3

A comparison of the Stage 1 and Stage 3 DEA results shows that the environmental adjustment changed the estimated efficiency levels of the hospitals. For pure technical efficiency (PTE), the mean Stage 3 score was higher than the Stage 1 score in every year. The increase ranged from 0.076 in 2019 to 0.146 in 2021. Mean technical efficiency (TE) also increased consistently after adjustment, with the difference becoming larger toward the end of the study period, particularly in 2021 and 2022. Scale efficiency (SE) showed only small changes in the earlier years but generally improved from 2019 onward, with the largest increase observed in 2022.

Overall, the Stage 3 results indicate that adjusting for environmental conditions and statistical noise led to higher estimated efficiency for most of the observed periods, especially for PTE and TE. This suggests that part of the inefficiency observed in Stage 1 was associated with differences in the external operating environment rather than hospital management alone.

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Comparison of Efficiency Scores: Stage 1 vs. Stage 3

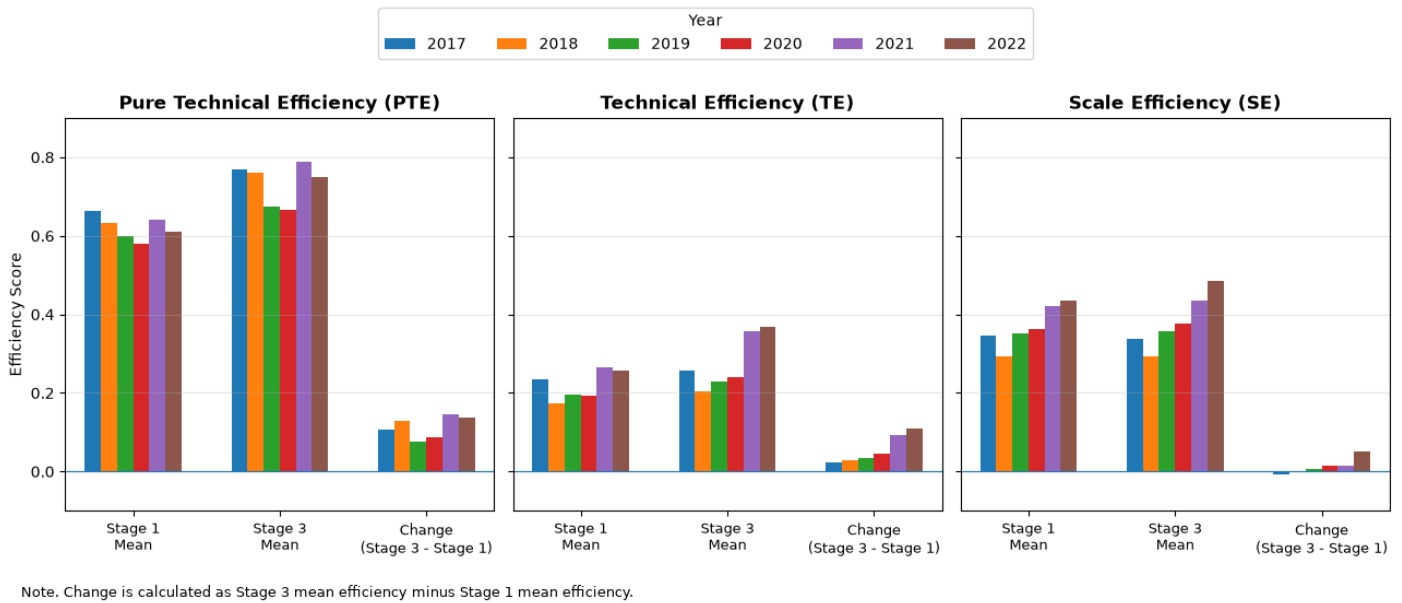


Figure 2. Comparison of Efficiency Scores: Stage 1 vs. Stage 3

To statistically examine the change in the main VRS/BCC efficiency measure, a Wilcoxon signed-rank test was applied to the paired Stage 1 and Stage 3 PTE scores. The test showed a statistically significant difference between the two stages ($z = -11.064$, $p < 0.001$).

Table 8. Statistical Test Results — Wilcoxon Signed-Rank Test (Stage 1 vs. Stage 3)

Rank category	Observations	Sum of ranks	Expected
Positive ranks	11	496.0	8,627.5
Negative ranks	159	16,759.0	8,627.5
Zero differences	16	136.0	136.0
Total	186	17,391.0	17,391.0

Ho: Stage-1= Stage-3 $z = -11.064$; Prob > $z = 0.0000$ (Exact probability = 0.0000)

3.4 Malmquist Productivity Index (MPI) Results

The Malmquist productivity analysis shows that productivity generally improved across the 31 public hospitals during the study period. At the hospital level, 29 of the 31 hospitals recorded an average MEPI greater than 1, while one hospital had a value equal to 1 and only one hospital recorded a value below 1. The highest average MEPI was observed for DMU15 (1.43), followed by DMU14 (1.37) and DMU9 (1.35), whereas DMU28 recorded the lowest value (0.87). These results indicate that productivity growth was widespread across the hospital sample.

The TECH component was greater than 1 in 20 hospitals and below 1 in 11 hospitals. The highest TECH value was recorded by DMU14 (1.21), followed by DMU15 (1.18) and DMU9 (1.16). By contrast, relatively low TECH values were observed for DMU22 (0.80), DMU19 (0.84), and DMU31 (0.88). This suggests that improvements in the technology-related component were not uniform across hospitals.

TECCH showed a stronger overall pattern, with values above 1 in 29 of the 31 hospitals. The highest TECCH values were recorded by DMU30 (1.73), DMU27 (1.70), and DMU9, DMU19, and DMU29 (1.68). Only DMU6 (0.93) and DMU28 (0.92) had TECCH values below 1. Overall, the hospital-level results indicate that productivity improvement was driven more strongly by changes in efficiency performance than by the TECH component alone. Time-Series Trends in Malmquist Productivity Index (MPI) Components are presented in Figure 3.

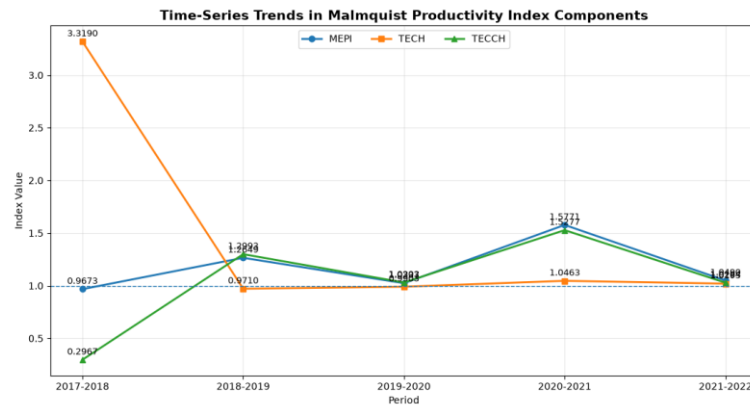


Figure 3. Time-Series Trends in Malmquist Productivity Index (MPI) Components

The time-series results also reveal considerable variation across periods. MEPI was below 1 only in 2017–2018 (0.9673), then increased to 1.2649 in 2018–2019 and remained above 1 thereafter. After a moderate value of 1.0237 in 2019–2020, MEPI reached its highest level in 2020–2021 at 1.5771, before declining to 1.0490 in 2021–2022. This pattern indicates that the strongest productivity improvement occurred during the 2020–2021 transition.

The TECH component was exceptionally high in 2017–2018 (3.3190), but declined to 0.9710 in 2018–2019 and 0.9903 in 2019–2020. It then recovered slightly to 1.0463 in 2020–2021 and 1.0195 in 2021–2022. TECCH showed the opposite initial pattern, with a very low value of 0.2967 in 2017–2018, followed by a substantial increase to 1.2993 in 2018–2019. It remained above 1 thereafter and peaked at 1.5277 in 2020–2021 before declining to 1.0284 in 2021–2022.

Table 8. Hospital-Level Malmquist Productivity Index (MPI) Results

DMU	MEPI	TECH	TECCH	DMU	MEPI	TECH	TECCH
DMU1	1.17	1.09	1.38	DMU17	1.20	1.08	1.55
DMU2	1.32	1.13	1.45	DMU18	1.19	1.08	1.39
DMU3	1.20	1.05	1.41	DMU19	1.04	0.84	1.68
DMU4	1.21	1.12	1.63	DMU20	1.15	1.04	1.40
DMU5	1.18	1.08	1.48	DMU21	1.32	1.15	1.58
DMU6	1.12	1.14	0.93	DMU22	1.00	0.80	1.35
DMU7	1.21	1.07	1.36	DMU23	1.10	0.89	1.41
DMU8	1.24	1.09	1.49	DMU24	1.11	0.98	1.41
DMU9	1.35	1.16	1.68	DMU25	1.04	0.89	1.28
DMU10	1.22	1.13	1.58	DMU26	1.19	1.03	1.64
DMU11	1.23	1.11	1.53	DMU27	1.11	0.96	1.70
DMU12	1.26	1.13	1.46	DMU28	0.87	0.90	0.92
DMU13	1.13	0.95	1.55	DMU29	1.12	0.99	1.68
DMU14	1.37	1.21	1.26	DMU30	1.11	0.92	1.73
DMU15	1.43	1.18	1.39	DMU31	1.10	0.88	1.66
DMU16	1.20	1.08	1.57				

MEPI: Malmquist Efficiency and Productivity Index (Total Factor Productivity Change); TECH: Technical Efficiency Change; TECCH: Technical Change (frontier shift). Values > 1 indicate improvement; values < 1 indicate regression.

Taken together, the Malmquist results show that productivity change was positive for most hospitals and most periods, but the relative contribution of TECH and TECCH varied considerably over time. In particular, the sharp productivity increase in 2020–2021 coincided with a strong rise in TECCH, while the unusually high TECH value in 2017–2018 was accompanied by a comparatively low TECCH value.

Based on the foregoing analytical results, the following section discusses the implications of the findings from both academic and policy perspectives.

4. DISCUSSION AND IMPLICATIONS

4.1 Discussion

The most important finding of this study is that hospital efficiency changed substantially after environmental adjustment. Stage 3 PTE exceeded Stage 1 PTE in every year from 2017 to 2022, and the paired Wilcoxon signed-rank test confirmed a statistically significant difference between the two stages ($z = -11.064$, $p < .001$). This indicates that part of the inefficiency observed in conventional DEA reflected environmental heterogeneity and stochastic effects rather than managerial performance alone. This interpretation is consistent with the three-stage DEA framework, which separates environmental effects and statistical noise from managerial inefficiency [10], and with evidence showing that hospital efficiency estimates can change after environmental adjustment [11].

The Stage 2 SFA results further demonstrate that resource use is shaped by structural conditions surrounding each hospital. Geographic remoteness, local labour-market conditions, population ageing, and differences in population concentration were associated with specific input slacks. In the Mongolian context, these findings are particularly relevant because hospitals in remote and sparsely populated areas may need to maintain beds and clinical staff to ensure minimum service availability and emergency preparedness even when patient volumes are relatively low. Therefore, apparent input redundancy should not automatically be interpreted as poor internal management.

A further contribution of the study is the inclusion of financial expenditure and revenue alongside physical and human resources. This extends the interpretation of efficiency from a purely technical perspective toward a broader resource-allocation perspective. Hospitals that deliver similar volumes of care may consume substantially different amounts of financial resources, and this difference cannot be fully captured by staff and bed indicators alone. By incorporating financial variables, the analysis provides a more economically meaningful assessment of how public resources are transformed into healthcare services.

The COVID-19 period requires particular caution in interpretation. In the main TVD-SFA model, the COVID period was significantly associated with nurse slack ($\beta = -5.4562$, $p < .01$) and other-staff slack ($\beta = 5.8845$, $p < .05$), suggesting that different workforce groups were affected in different ways. During the pandemic, official headcounts may not have reflected effective workforce availability because of infection, quarantine, redeployment, and additional infection-control duties. At the same time, patient demand changed sharply. In South Korea, outpatient utilization fell by about 15.7% and inpatient utilization by 11.6% during the early pandemic period [20], while Turkish public hospitals experienced declines of 39% in outpatient services and 29% in inpatient services in 2020 compared with 2019 [19]. These findings support the interpretation that pandemic-period efficiency changes may reflect simultaneous disruptions in labour availability and service demand rather than changes in management quality alone.

The Malmquist results also show that productivity growth was not uniform over time. MEPI was below 1 in 2017–2018 but exceeded 1 in all subsequent periods, reaching its highest level of 1.5771 in 2020–2021. During that period, TECH was 1.0463 and TECCH was 1.5277, indicating that frontier shift contributed more strongly to productivity growth than efficiency catch-up. This pattern is consistent with the Malmquist framework, which decomposes productivity change into technical efficiency change and technological change [18]. Accordingly, the observed productivity increase should be interpreted as a combination of changes in technology, service organization, resource deployment, and recovery in hospital activity rather than as a purely managerial improvement.

4.2 Implications

First, public hospital benchmarking should rely on environment-adjusted efficiency rather than raw DEA scores alone. The significant difference between Stage 1 and Stage 3 PTE indicates that hospitals operating under different structural conditions may receive different efficiency scores even when their internal performance is similar. Therefore, benchmarking and performance-based financing should compare hospitals within reasonably similar operating environments.

Second, incorporating financial indicators makes the analysis more relevant for public resource allocation. Efficiency assessment should consider not only how many services are produced, but also how much financial resource is required to produce them. This is particularly important for identifying whether differences in performance arise from technical resource use, financial resource use, or both.

Third, workforce and technology policies should be interpreted jointly rather than separately. The contrasting pandemic-related changes in nurse and other-staff slack show that workforce groups may respond differently to system shocks, while the strong TECCH value in 2020–2021 highlights the importance of changes in the production frontier. For policy, this implies that investments in equipment, information systems, and digital infrastructure should be combined with staff training, flexible workforce deployment, and workflow redesign if productivity gains are to be sustained.

5. CONCLUSION

5.1 Main findings

This study applied an integrated three-stage DEA, SFA, and Malmquist Productivity Index framework to a balanced panel of 31 Mongolian public hospitals from 2017 to 2022. After adjustment for environmental conditions and statistical noise, pure technical efficiency increased in every year, and the difference between Stage 1 and Stage 3 was statistically significant ($z = -11.064$, $p < .001$). This indicates that part of the inefficiency identified by conventional DEA may reflect operating conditions beyond the direct control of hospital management rather than managerial performance alone. The three-stage DEA framework is designed to separate environmental effects and statistical noise from managerial inefficiency [10].

Productivity change was also uneven over time. Overall productivity declined slightly in 2017–2018 but increased in all subsequent periods, with the strongest improvement observed in 2020–2021. This pattern is unlikely to reflect a single mechanism and may instead result from simultaneous changes in service recovery, resource allocation, workforce organization, financing, and patient flows.

5.2 Academic contribution

The principal academic contribution of this study lies in integrating environmental adjustment, stochastic noise, and longitudinal productivity change within a single framework for evaluating Mongolian public hospitals. This allows hospital performance to be interpreted beyond a single raw DEA score and reduces the risk of attributing environmentally induced inefficiency directly to management. Previous methodological work has emphasized that efficiency comparisons may be distorted when heterogeneous operating environments are not properly accounted for [10].

The study also adds an economic dimension by incorporating financial expenditure and revenue together with physical and human resources. This extends the analysis from a purely technical assessment of hospital capacity toward an evaluation of how resources are transformed into services and financial outcomes.

5.3 Economic and policy implications

Including financial variables makes it possible to distinguish hospitals that produce similar service volumes with different levels of resource expenditure. The analysis therefore provides information not only on how much care is delivered, but also on the economic resources required to generate that care.

From a policy perspective, unadjusted DEA rankings should not be used mechanically to justify reductions in budgets, beds, or staffing. Hospitals in remote or sparsely populated areas may need to maintain reserve capacity to ensure emergency access and minimum service availability even when average utilization is low. Performance-based financing and benchmarking should therefore compare hospitals operating under reasonably similar structural conditions.

This consideration is particularly important during the COVID-19 period. Stable or increasing physician and nurse headcounts may have coincided with lower patient volumes because of restrictions on elective care, reduced

healthcare-seeking behaviour, quarantine, infection-control measures, and workforce disruption. In such circumstances, lower output per staff member should not automatically be interpreted as excess staffing or managerial failure. International evidence documents substantial disruptions in healthcare utilization during the pandemic, with direct implications for measured hospital efficiency [19,20].

5.4 Limitations

Several limitations should be acknowledged. First, the sample is limited to general public hospitals and does not represent specialized infectious-disease hospitals, tertiary institutions, or private hospitals. Pandemic effects may therefore have been more pronounced in facilities directly responsible for infectious-disease and COVID referral care. Second, the financial input is based on officially recorded budget expenditure. Emergency and disaster funds, locally financed resources, international assistance, donations, equipment, and other in-kind support may not have been fully captured in routine expenditure statistics. The actual resources used during the pandemic may therefore have exceeded the financial inputs observed in the dataset.

Third, official staff headcounts may not fully represent effective workforce capacity. Infection, quarantine, shift restructuring, additional infection-control responsibilities, and staff redeployment may have altered the amount of labour actually available for routine hospital services.

Finally, comparable institution-level statistics after 2022 were not consistently available in a form suitable for extending the balanced panel, and some detailed data were subject to access and confidentiality restrictions. Consequently, the study could not examine post-pandemic recovery over a longer horizon.

5.5 Future research

Future research should first establish peer-based benchmarking groups defined by hospital size, service profile, geographic context, and population catchment. This would allow high-performing hospitals to be compared with genuinely comparable institutions and help identify specific resource-allocation and management practices associated with better performance.

A broader extension should move beyond individual hospitals toward the efficiency of actual health-budget expenditure in Mongolia. Future research could combine central government health expenditure, Health Insurance Fund financing, local government resources, capital investment, and, where measurable, external assistance, and relate these resources to regional healthcare outputs. Such an approach would make it possible to assess how effectively actual health expenditure is transformed into healthcare services at provincial and national levels and would extend the current hospital-efficiency framework toward a broader analysis of public health resource-allocation efficiency.

Declaration on the Use of AI-Assisted Tools

Generative AI-assisted tools were used solely for English translation, language editing, grammatical refinement, and formatting support. The authors independently developed the research design, conducted the statistical analyses, interpreted the results, verified all references, and take full responsibility for the final content of the manuscript.

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Appendix Table A1. Stage 2 Time-Invariant SFA Results

Variable	Bed Slack	Physician Slack	Nurse Slack	Other Staff Slack	Cost Slack
Urban	3.3491	2.1323	−1.2667	5.2012	−27.3955
	(9.9032)	(2.0502)	(4.0930)	(5.4695)	(37.0076)
GDP	−0.0001	−0.0000	−0.0001	−0.0006**	−0.0038**
	(0.0006)	(0.0001)	(0.0002)	(0.0003)	(0.0017)
Land area	0.0843	−0.0005	−0.0223	0.0506	0.4594
	(0.0755)	(0.0166)	(0.0281)	(0.0419)	(0.2929)
Population density	0.8975	−0.1185	−1.2669	5.5481**	27.0965
	(4.3703)	(0.9204)	(1.8206)	(2.7246)	(17.2602)
Unemployment	0.6610	−0.0104	0.0365	0.0152	2.6702*
	(0.5544)	(0.1016)	(0.1556)	(0.2737)	(1.5198)
Distance to capital	0.0069	0.0016	0.0075***	0.0042	−0.0143
	(0.0072)	(0.0018)	(0.0029)	(0.0043)	(0.0276)
Population aged 65+	0.0003	0.0001	0.0001	−0.0005	−0.0010
	(0.0008)	(0.0002)	(0.0003)	(0.0005)	(0.0027)
COVID-19 dummy	14.0730***	1.8546**	−5.0434***	8.2969***	79.5152***
	(4.7386)	(0.8423)	(1.2605)	(2.1452)	(12.1587)
Observations	186	186	186	186	186
Log likelihood	−891.254	−576.096	−647.274	−754.515	−1072.667

AUTHOR'S INTRODUCTION

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	Uranchimeg Bolorchimeg is a PhD Candidate in the Department of Business Administration at Incheon National University, Republic of Korea. Her research focuses on healthcare efficiency, productivity, data envelopment analysis, and public-sector performance. This article draws on her doctoral research using Mongolian public-hospital data from 2017–2022. She led conceptualization, data preparation, empirical analysis, and manuscript drafting.	

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	Young Kyun Kim is a Professor in the Department of Business Administration at Incheon National University, Republic of Korea. His academic role in this study included research supervision, methodological guidance, interpretation of results, and critical review of the manuscript. He contributed to strengthening the study design and the presentation of findings on hospital efficiency and productivity.	