Data Envelopment Analysis for Sustainable Healthcare: Ranking Hospitals based on CO_2 Emissions; Desirable/Undesirable Output

F. Masoudian, K. Lennerts

Institute of Technology and Management in Construction / Facility Management, Karlsruhe Institute of Technology, Karlsruhe, Germany

Abstract:

Performance management in hospitals can help optimize healthcare delivery, efficient resource allocation, and sustainability, especially in the growing operational and environmental challenges. A comprehensive review of performance measurement tools and techniques in healthcare shows that among quantitative techniques, data envelopment analysis (DEA) has emerged as a widely used tool. DEA has emerged as a prominent method in recent literature due to its flexibility in handling multiple inputs and outputs, including both desirable and undesirable factors. This study applies a customized DEA model, capable of accounting for undesirable outputs, to evaluate the performance of hospitals participating in the OPIK project in 2023. The OPIK is an open, university-led benchmarking pool for technical managers of public hospitals in German-speaking countries. The study ranks these hospitals based on efficiency scores focused on CO2 emissions, an essential aspect of sustainability in healthcare facilities. The model ranks hospitals based on their efficiency and identifies benchmarks for inefficient hospitals. The results highlight the potential of DEA in addressing current challenges in healthcare performance management and contribute to the growing literature on healthcare performance evaluation.

Keywords:

Data Envelopment Analysis (DEA), Undesirable Output, Performance Management, Hospital Efficiency

1. Introduction

Performance management plays a central role in the strategic development and sustainability of healthcare systems worldwide. According to ISO 9004, performance is a measurable result that can relate either to quantitative or qualitative findings concerning the management of activities, processes, products, services, systems, or organization (ISO 9004: 2018). This definition highlights the flexibility and scope of performance indicators, which are especially crucial in hospitals; highly complex and resource-intensive entities, that are fundamental for delivering healthcare. Hospitals consume an excessive share of healthcare expenditures and are simultaneously under pressure to improve clinical quality, reduce costs, and minimize their environmental impact, all while delivering healthcare services efficiently and meeting population needs.

Hospitals are the cornerstone of any health system, consuming a large share of resources while striving to deliver high-quality care. They account for 30–80% of total health spending (Hadian et al. 2025) and often face financial deficits even as they pursue quality objectives (Almehwari et al. 2024). Effective performance management, including operational efficiency, throughput and cost control, is therefore critical. Indeed, improving hospital efficiency and containing costs has long been an international priority (Almehwari et al. 2024). Well-managed hospitals can reallocate savings to patient care, enabling investments in new technology and staffing that further enhance quality (Hadian et al. 2025).

Hospitals are also unusually complex and resource intensive which are open 24 hours and 7 days a week (Lennerts et al. 2009). As the most complex facilities in a healthcare system, hospitals have high occupancy, treat critical and varied cases, and involve complex building systems and equipment (Dolcini et al. 2025). They consume vast amounts of energy (second-highest per unit area of any industry) (Dolcini et al. 2025), and they must coordinate thousands of staff and processes. This cost intensity and complexity mean that performance management must balance many factors including financial, clinical and operational, without sacrificing quality. Moreover, hospitals increasingly must meet sustainability goals. The healthcare sector contributes about 5.2 % of global greenhouse gases (Dolcini et al. 2025), and in OECD countries hospitals alone are the largest source of that footprint (roughly 28–36 % of healthcare emissions) (Dolcini et al. 2025). Thus, performance metrics are expanding beyond

traditional efficiency to include environmental impact, especially as health systems commit to Net Zero targets (Dolcini et al. 2025; Mirow et al. 2024).

Carbon emissions and environmental impact are now key performance dimensions. Healthcare's own climate footprint can undermine public health, creating a strong rationale for including sustainability in hospital metrics (Dolcini et al. 2025; Mirow et al. 2024). For example, highly developed health systems (which serve rising patient needs) paradoxically contribute significantly to climate change (Mirow et al. 2024). Hospitals emit greenhouse gases directly (from on-site energy use) and indirectly through procurement and supply chains (Mirow et al. 2024). In practice, CO_2 emissions are emerging as an "undesirable output" that performance evaluations must account for. Global initiatives (e.g. WHO's Healthy Hospitals Healthy People campaign and Net Zero pledge) emphasize reducing hospital carbon as essential to broader climate goals. Consequently, assessing hospital performance increasingly means measuring both healthcare outputs (like treated patients and outcomes) and environmental outputs (like CO_2 emissions).

DEA is a powerful tool for such multidimensional performance evaluation. DEA is a non-parametric benchmarking method that compares "Decision-Making Units (DMUs)" (here, hospitals) based on multiple inputs and outputs (Hadian et al. 2025; Jung et al. 2023). It identifies the efficient frontier of best practice units and measures others' relative efficiency. Crucially, DEA can incorporate undesirable outputs (like emissions or waste) by treating them appropriately (for instance, as inputs or by directional distance functions). This flexibility makes DEA attractive for sustainable performance analysis. In healthcare, DEA has become a leading efficiency technique (Jung et al. 2023), widely applied to hospital benchmarking (Hadian et al. 2025; Jung et al. 2023). Unlike simpler ratios, DEA handles many resources (beds, staff, costs) and outcomes (admissions, survival rates) simultaneously. In our study, a special DEA was used to include CO_2 emissions as an undesirable output.

Finally, evaluating hospitals today means linking to ESG (Environmental, social, and governance) and sustainability targets. Hospitals are aiming for decarbonization (in line with national Net Zero policies) by investing in renewable energy, retrofitting buildings, and optimizing operations. In short, hospital performance is now viewed through an ESG lens, economic efficiency must go hand in hand with environmental stewardship and social responsibility. As Dolcini et al. argue, embedding

environmental sustainability into health performance systems helps operationalize and prioritize green goals (Dolcini et al. 2025). By integrating DEA-based efficiency analysis to CO_2 benchmarks and green building metrics, our work links traditional hospital performance evaluation with the broader sustainability agenda, in this study the focus is on environmental performance.

2. Literature Review

DEA was introduced in the late 1970s as a non-parametric frontier technique for measuring the relative efficiency of DMUs by Charnes et al., 1978 and has since become foundational in operations research and management (Mitakos & Mpogiatzidis 2024; Cook & Seiford 2009). Cook and Seiford's survey of 30 years of DEA research highlights its major developments (CCR, BCC models, multiplier restrictions, etc.) and broad applicability (Cook & Seiford 2009). Its flexibility, handling many inputs/outputs without pre-specified weights, has made DEA a standard tool across sectors.

DEA in Healthcare and Hospital Performance

DEA has been widely applied to evaluate hospitals' technical and scale efficiency. Early studies (and many classical papers) used input or output-oriented CCR/BCC models to score hospitals, often highlighting large variation and inefficiency in public health systems (Cook & Seiford 2009; Otay et al. 2017). Over time, scholars expanded DEA's scope in healthcare. For instance, Jahantigh and Ostovare (2020) evaluated 40 Tehran teaching hospitals by first using PROMETHEE II to rank performance factors, then applying an output-oriented DEA model (4 inputs, 8 outputs) to compute efficiency (Jahantigh & Ostovare 2020). Similarly, Peixoto et al. (2018) applied Principal Component Analysis (PCA) and cluster analysis within a DEA framework to assess 20 Brazilian university hospitals, grouping them by performance characteristics and highlighting diverse efficiency profiles across regions (efficiency of hospitals with major specialty services vs smaller units). These multivariate-DEA hybrids illustrate how DEA can be embedded in larger analyses (PCA for dimensionality reduction; clustering for taxonomy) to manage many variables and classify units for benchmarking (Peixoto et al. 2018).

Chronological Developments in Hospital DEA

The hospital DEA literature has evolved chronologically. Early 2000s–2010s: foundational reviews (e.g. O'Neill et al. 2008; Otay et al. 2017) established DEA as the

go-to tool for hospital efficiency analysis. Researchers applied CCR/BCC models to national hospital datasets (USA, Europe, etc.), often identifying very high average technical efficiency but also many inefficiencies due to excess inputs (beds, staff) or underutilization.

Recent years (2017–2023): focus has shifted to more complex models and contexts. Ghahremanloo et al. (2020) introduced a novel DEA-EEP model that simultaneously measures Efficiency, Effectiveness, and Productivity of hospitals (Ghahremanloo et al. 2020).

Other recent studies have compared DEA with parametric methods. For example, Moses et al. (2021) applied Stochastic Frontier Analysis (SFA) to estimate technical efficiency of Kenya's 47 county health systems, finding a median efficiency of ~84% and identifying declining efficiency trends in many counties (Moses et al. 2021).

A major theme is accommodating real-world complexities. Slack-based and non-radial DEA models, introduced by Tone (2001) and others, allow non-proportional changes and directly incorporate slacks (excess inputs or shortfall in outputs). Fang et al. (2024) applied a directional slacks-based measure (SBM) in a three-stage DEA to Chinese provincial health data (2012–2021) (Fang & Li 2024). A directional SBM, unlike radial DEA, can expand desirable outputs and contract undesirable ones without assuming radial changes. Similarly, many studies use additive or range-adjusted measures for hospitals to fully rank units. The Sustainability (2024) study on medical waste recycling explicitly notes that SBM is "particularly suitable for handling undesirable outputs" (Song et al. 2024), highlighting that slack-based, non-oriented DEA is well suited when some outputs (e.g. pollution or waste) should decrease rather than increase.

DEA and Undesirable Outputs (Sustainability)

The literature increasingly recognizes undesirable outputs in healthcare; such as waste generation, emissions, or negative patient outcomes, and incorporates them in DEA. During the COVID-19 pandemic, scoping reviews found a clear shift toward including undesirable factors (e.g. mortality rates) in DEA models (Mitakos & Mpogiatzidis 2024). Mitakos & Mpogiatzidis (2024) report that researchers explicitly added hospital mortality (an undesirable output) and other quality-of-care metrics into efficiency models to obtain a more holistic performance view (Mitakos & Mpogiatzidis 2024).

For example, Yu et al. (2020) analyzed Chinese hospital productivity using a meta-frontier DEA and Malmquist–Luenberger index, including atmospheric pollution from incinerating medical waste as an undesirable output (Yu et al.2020). Monzeli et al. (2025) similarly incorporated both desirable and undesirable outputs in a DEA of 30 Tehran emergency wards, emphasizing that explicitly modeling waste/cost factors leads to more accurate efficiency comparisons (Monzeli et al. 2025). They note that including undesirable inputs/outputs "significantly influences the identification of the efficiency frontier", providing a "more accurate reflection of real-world constraints (Monzeli et al. 2025).

3. Methodology

In DEA, an efficient DMU produces maximal desirable outputs for given inputs or, equivalently, uses minimal inputs for given outputs. The Slack-Based Measure (SBM) model introduced by Tone (2001) (Ma et al. 2018), is adopted because it is *non-radial* and handles input/output slacks directly. Unlike classical radial DEA models (CCR/BCC) that assume proportional changes in all inputs/outputs, the SBM model explicitly accounts for excess inputs and shortfalls in outputs (Yu et al. 2020, Ma et al. 2018). This feature is crucial here, as *excess* capacity (e.g. unused beds, surplus electricity usage) or *insufficient* outputs (patients served) may be present in hospitals, and these slacks need to be quantified.

Importantly, both desirable outputs (inpatients and outpatients) and an undesirable output (CO_2 emissions) are included. The SBM framework accommodates undesirable outputs without data transformation. It treats them like outputs that should be *minimized* rather than maximized (Yu et al. 2020, Żyłowski et al. 2023). In other words, efficiency improves when a hospital reduces CO_2 emissions (an undesirable "output") while maintaining or increasing patient services. Tone (2004) showed that SBM can handle non-separable desirable and undesirable outputs simultaneously (Ma et al. 2018), and recent studies in healthcare advocate this approach for environmental impacts (Yu et al. 2020; Żyłowski et al. 2023).

We consider 12 DMUs, denoted by the index j, where j ranges from 1 to n. For each hospital (DMU) denoted by subscript 0, let the input vector be $x_{i0}(i = 1, \cdots, m)$ where $m = 2$ (number of beds, electricity consumption), the desirable (good) outputs $y_{g0}(g = 1, \cdots, s)$ where $s = 2$ (inpatients, outpatients), and the undesirable (bad) output

$b_{b0}(b = 1, \cdots, t)$ where $t = 1$ (CO_2 emissions). We introduce slack variables $s_i^- \geq 0$ for input excesses, $s_g^+ \geq 0$ for desirable output shortfalls, and $s_b^- \geq 0$ for excess undesirable outputs [20].

Under the assumption of constant returns to scale (CCR technology), the SBM efficiency score ρ for DMU_0 is obtained by:

1) Objective: $min\, \rho$
2) Constraints:

2. 1. $$x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \,, \forall i \in I$$

2. 2. $$y_{g0} = \sum_{j=1}^{n} y_{gj}\lambda_j - s_g^+ \,, \ \forall g \in G$$

2. 3. $$b_{b0} = \sum_{j=1}^{n} b_{bj}\lambda_j + s_b^- \,, \forall b \in B$$

2. 4. $$\rho \cdot \left(1 + \frac{1}{s}\sum_g \frac{s_g^+}{y_{g0}} + \frac{1}{t}\sum_b \frac{s_b^-}{b_{b0}}\right) = 1 - \frac{1}{m}\sum_i \frac{\bar{s}_i}{x_{i0}}$$

Here $n = 12$ is the number of hospitals (DMUs) in our sample, $\lambda_j \geq 0$ are intensity variables combining peer hospitals to form a reference, and s_i^-, s_g^+, s_b^- are the respective slacks. These constraints ensure that each hospital's inputs and outputs are compared to a convex combination of other hospitals; input slacks s_i^-represent excess input over the reference mix, output slacks s_g^+ represent shortfall in good outputs, and s_b^- represents excess undesirable output. All slacks are equal or greater than 0 and $\lambda_j \geq 0$. This formulation naturally minimizes inputs (through s_i^-) and maximizes desirable outputs (through s_g^+), while minimizing the undesirable output slack s_t^b.

By construction, SBM does not require any ad-hoc transformation of undesirable variables (e.g. taking reciprocals or treating them as inputs) (Żyłowski et al. 2023). Instead, it directly incorporates CO_2 emissions as an output slack to be reduced. This preserves the physical interpretation of each variable. Tone (2004) and others argue that SBM yields a unique efficiency score that reflects both kinds of slacks, and is thus well-suited when both input excess and undesirable outputs exist [19]. Empirical studies in healthcare efficiency under environmental constraints likewise employ non-radial SBM models with undesirable outputs (Yu et al. 2020, Ma et al. 2018). Cooper *et al.* (2011) note that advanced DEA models (such as SBM) have been developed to

address multiple inputs/outputs and relaxation of proportionality assumptions, which is important in contexts like hospitals. In summary, the SBM model allows us to rank hospitals by a single efficiency index that rewards lower inputs, higher patient outputs, and lower CO_2 emissions simultaneously.

We also adhere to common DEA practice regarding sample size. A frequently cited rule-of-thumb is $n \geq max\ \{m \times s, 3(m+s)\}$ (Wong 2021). For our case $m = 2$, $s + u = 3$ (treating the one undesirable output as an "output" in the formula), this rule gives $n \geq max\ \{2 \times 3, 3(2+3)\} = 15$. Our dataset has $n = 12$ hospitals, which falls slightly below this threshold. While many DEA applications proceed with is $n < max\ \{m \times s, 3(m+s)\}$, we note this as a limitation; a smaller n relative to $m + s$ may reduce discrimination among units (Wong 2021). Nonetheless, the SBM approach remains valid; we interpret efficiency scores with this caution in mind. To assess the impact of sample size in this study, sensitivity tests were conducted using subsets of three DMUs. The SBM model continued to yield varying efficiency scores rather than classifying all units as efficient, suggesting that the homogeneity and similarity of hospitals in this dataset reduce the risk of trivial efficiency classification.

It should be noted, however, that if a larger number of hospitals were available, some units currently labeled efficient might no longer achieve efficient status in a more discriminatory setting. Accordingly, the results are interpreted cautiously and viewed as exploratory rather than definitive.

By explicitly incorporating CO_2 as an undesirable output, this model operationalizes the environmental pillar of ESG performance. The resulting efficiency scores thus capture not only operational effectiveness but also the environmental sustainability of each hospital.

4. Data and variables

The input–output data come from the KIT OPIK project (Open Benchmarking Round for hospitals). OPIK is a German-speaking hospital benchmarking network coordinated by the Karlsruhe Institute of Technology. Participants report facility metrics via a shared database. For 2023, twelve hospitals provided complete data and were included in our analysis. Our inputs are Beds (number of hospital beds in operation) and Electricity consumption (kWh), representing key resource usages. The desirable outputs are Inpatients (number of overnight-stay patients treated) and Outpatients (number of

outpatient cases). The single undesirable output is CO_2 Emissions associated with the hospital's energy use (in metric tons). We assume that more inpatients/outpatients is better, while more CO_2 is worse. (All hospitals operated in a similar regulatory environment, so we use a constant returns to scale (CRS) model. These variables reflect standard practice in environmental healthcare DEA. For example, inpatients/outpatients capture service output, and energy-related CO_2 is a measurable byproduct of hospital operations (Yu et al. 2020; Żyłowski et al. 2023).

The data for the model are presented in Table 1. To ensure the anonymity of the hospitals, the values have been normalized by dividing them by their respective minimum, thereby obscuring direct identification while preserving relative relationships.

Table 1- Input values to solve the model

DMUs	***Inputs***		***Desirable outputs***		***Undesirable outputs***
	# of Beds	***Electricity Consumption***	***Outpatients***	***Inpatients***	***CO_2 Emission***
H1	2.9936	3.6804	3.9919	2.9404	3.3600
H2	1.0000	2.5365	4.7067	1.3920	2.3202
H3	1.5227	3.0670	1.3175	1.3706	3.1225
H4	1.8745	4.1114	2.1315	1.8968	4.3841
H5	1.3818	4.0655	1.4143	1.1801	4.3058
H6	1.5227	1.0000	1.0715	1.1985	1.1661
H7	1.4509	1.5039	1.0000	1.1539	1.5302
H8	1.0000	3.5776	1.7104	1.0000	3.9433
H9	1.2273	5.0042	1.2490	1.3462	4.0601
H10	1.3191	2.7888	1.5001	1.2096	8.1725
H11	1.3755	4.1138	2.6727	1.0765	3.9688
H12	1.4855	1.2268	1.2980	1.0572	1.0000

5. DEA structure

For clarity, one can imagine plotting each hospital in a multi-dimensional input-output space and then drawing an *efficiency frontier* through the best-performing points. Hospitals on the frontier (efficiency=1) have no slacks and represent best practice.

They produce the most health services with least resource waste and emissions. Hospitals below the frontier have gaps. The SBM framework constructs this frontier via linear programming and computes for each hospital how much its inputs or outputs could be improved (i.e. how much slack would need to be eliminated) (Ma et al. 2018; Żyłowski et al. 2023). In the analysis, an efficiency score for each hospital is obtained, and the peer hospitals or reference sets have also been identified. Indeed associated input/output targets required to reach the frontier, including output augmentations and input/emission reductions derived from the slacks.

6. Results and Discussion

Table 2 presents the efficiency scores (ρ) for each of the 12 hospitals along with their reference sets under the constant returns to scale (CRS) slack-based DEA model. The efficiency score is a relative measure between 0 and 1, where 1 (or 100%) represents a hospital on the efficient frontier (best practice) and values below 1 indicate the proportion of performance relative to that frontier.

Table 2- Efficiency scores and reference sets

Hospital	*Efficiency (ρ)*	*Reference set (peer DMUs)*
H1	**1.00**	**H1**
H2	**1.00**	**H2**
H3	**0.29**	**H2**
H4	**0.34**	**H2**
H5	**0.23**	**H2**
H6	**1.00**	**H6**
H7	**0.53**	**H2, H6**
H8	**0.30**	**H2**
H9	**0.23**	**H2**
H10	**0.28**	**H2**
H11	**0.30**	**H2**
H12	**1.00**	**H12**

Each inefficient hospital's reference set in Table 1 identifies the efficient peer(s) that form the benchmark for that hospital. The reference set is essentially the peer group or combination of best-practice hospitals that the DEA model uses to project the inefficient hospital onto the efficiency frontier. For instance, Hospital H7 ($\rho = 0.53$) has a reference set of {H2, H6}, meaning that a composite of efficient hospitals H2 and H6 (with some weighting λ) defines the performance target for H7. In practical terms, H7 should strive to emulate the practices of H2 and H6 (H2 in certain aspects and H6 in others) to improve its efficiency. The presence of multiple units in a reference set implies that no single peer had the same input-output profile to dominate; instead, a convex combination of peers is needed. This is common in DEA, an inefficient DMU is often benchmarked against a mix of efficient DMUs, each contributing to the target. If only one peer is listed (as with H3 referencing H2), it indicates that a single efficient hospital (H2) was sufficient to serve as the benchmark for that DMU's improvement. The concept of the reference set is valuable for managers because those peer units can highlight the weak aspects of the inefficient hospital's performance and provide concrete targets.

Slack Values and Performance Gaps

While the efficiency score ρ tells us *how far* a hospital is from the frontier, the slack values in Table 3 reveal *where* and *how* a hospital is inefficient. Table 3 lists the slack for each input and output for all hospitals. Slack represents excess inputs or shortfalls in outputs that remain even after a hospital is radially projected onto the frontier. In the context of an SBM model, any non-zero slack indicates an inefficiency in that specific dimension. An efficient hospital will have no slacks in any input or output. It means it is impossible to improve any input or output without worsening another. Whereas an inefficient hospital typically has one or more slacks, indicating waste or underperformance in those categories.

Positive input slack indicates an *excess* amount of that input (unused resource that could be reduced), while a positive good-output slack indicates a *shortfall* (output that could be increased). A positive undesirable output slack (CO_2) indicates an excess of emissions that should be cut down. All values are in the original units of each measure.

Table 3- Input and output slack values

Hospital	*Beds*	*Electricity*	*Outpatients*	*Inpatients*	*CO2*
H1*	0	0	0	0	0
H2*	0	0	0	0	0
H3	591.82	9.28	654619.41	5.5	10053.46
H4	563.03	1.06	845068.49	0	14669.06
H5	587.42	3.12	508328.87	0	28065.29
H6*	0	0	0	0	0
H7	316.03	0	275124.79	0	328.75
H8	309.73	2.86	329720.36	0	27316.68
H9	286.15	4.15	651778.35	0	21794.47
H10	495.07	9.52	511069.49	0	73873.62
H11	662.31	3.50	190861.76	0	26093.26
H12	0	0	0	0	0

Interpretation of Efficiency and Reference Sets

A score less than 1 implies relative inefficiency. The hospital could improve by either reducing inputs, increasing outputs, or both. The reference set tells us *who* the hospital should emulate. For H7, the reference set {H2, H6} means that some weighted blend of Hospital 2 and Hospital 6's performance was used as the benchmark. If a hospital's reference set contains multiple peers, it often implies that no single peer was a perfect role model on its own; the hospital may need to adopt different best practices from multiple sources. This is a common scenario; one peer might excel in operational efficiency (input usage) and another in service output, and the combination sets a holistic target. Identifying these peer units is extremely useful for benchmarking. They effectively form a peer benchmark group for the inefficient hospital. Hospital managers

can look at the practices of each peer to understand which changes could yield the improvements indicated by the slacks.

Benchmarking and Managerial Insights

The findings from this DEA-SBM analysis can help craft targeted benchmarking strategies. Each inefficient hospital has a custom roadmap. Its efficiency score tells how much improvement is needed overall; its reference peers show who to learn from; and its slacks detail what to improve and by how much. Managers can set specific improvement targets such as “reduce electricity use by X kWh per year” or “increase inpatient admissions by Y%” based on the slack values. Because DEA provides *quantitative targets*, it moves beyond vague suggestions for inputs and outputs.

By comparing to peer hospitals, there is also a learning aspect, sometimes called *benchmarking to best practice*. If one hospital’s peers all achieve significantly higher outpatient visits per physician than it does, that points to exploring what those peers are doing differently (perhaps they have better scheduling systems or use telehealth, etc.). In this regard, the DEA results promote knowledge transfer, inefficient units have concrete examples of better-performing models. This peer benchmarking is one of DEA’s strengths, as it not only labels units as inefficient but also tells each one *how to become efficient* by emulating others.

Finally, it is worth noting the role of returns to scale in improvement strategy. Under the CRS assumption, some hospitals may be inefficient partly due to scale mismatches. In the context of this study, if any smaller regional hospital was inefficient, the solution might be to increase its catchment area or services to utilize resources fully. These strategic decisions are supported by DEA analysis, we can identify whether inefficiency is mostly due to poor internal performance (slacks) or an inappropriate scale of operation. In sum, the DEA-SBM with undesirable outputs, provides a comprehensive performance evaluation. It identifies not just *how efficient or not* each hospital is, but pinpoints *why* and *in what ways* they are inefficient and offers insight into *how* to improve along both operational and environmental dimensions.

7. Conclusion

This study evaluated the performance of 12 hospitals using a CRS slacks-based DEA model that accounted for both desirable (outpatient and inpatient) and undesirable

outputs (CO_2 emissions). The *Results and Discussion* above highlighted that 4 of 12 hospitals were fully efficient, while the remaining hospitals exhibited varying degrees of inefficiency. By examining efficiency scores, peer reference sets, and slack values, we gained understanding of each hospital's performance shortcomings. In summary, the DEA results indicate that many hospitals are operating below their potential, it means using more resources than necessary and/or not producing as much health service as they could, and there is significant room for improvement in both operational and environmental dimensions.

Key findings is that several hospitals have *excess inputs* indicating that resources are not being utilized to their fullest extent. At the same time, many have *output shortfalls*, especially in outpatient visits, suggesting that these hospitals could serve more patients with the resources at hand. The incorporation of CO_2 as an undesirable output proved insightful that a number of hospitals that were technically efficient in service delivery were found to be environmentally inefficient, emitting more CO_2 than the best-practice level. This indicates hidden inefficiency. Traditional models ignoring bad outputs would miss and underscores the importance of including environmental performance in the evaluation of healthcare efficiency.

The analysis provides concrete guidance for hospitals striving to improve. First, reducing operational inefficiencies is vital as hospitals with excess capacity (e.g. unused beds or staff downtime) should seek to either scale down those inputs or increase patient volume to utilize them. This might involve budget reallocations, process improvements, or even structural changes like consolidating departments. This dual focus on operational and environmental efficiency reflects a modern view of hospital performance that values sustainability alongside productivity.

One of the strengths of this DEA evaluation is its capacity to facilitate peer learning. Each inefficient hospital has been associated with one or more best-practice peers. For hospital administrators and clinicians, this provides a very tangible starting point, they can initiate knowledge exchange with the identified peer institutions to understand how those hospitals achieve superior performance. If a hospital's peers are, say, particularly good at managing outpatient workflows (resulting in no outpatient slack), a visit or case study review could reveal specific innovations (like advanced scheduling systems, better integration with primary care, etc.) that could be adopted.

Our use of the CRS model means the efficiency scores reflect overall technical efficiency without isolating scale effects. The results suggest that some hospitals might be operating on a suboptimal scale. Policymakers can use these insights to ensure that the hospital network is well-balanced, meaning that neither overly concentrating services in a few large centers nor spreading resources too thin across many small units. In practice, combining this study's results with a variable-returns DEA or other scale analysis could pinpoint which hospitals have scale issues. For now, a prudent recommendation is that each hospital's leadership reflects on whether their institution's size is appropriate given its performance.

In closing, the DEA CRS SBM model with undesirable outputs has proven to be a powerful tool for evaluating and discussing hospital performance. It provides a comprehensive perspective that encompasses both efficiency in healthcare delivery and environmental stewardship. The results and discussion offered a detailed look at where hospitals can improve; from cutting excess resource use to boosting patient care delivery to reducing carbon emissions.

In the current context, ESG performance has become increasingly important for healthcare institutions. This study demonstrates that environmental performance can be quantitatively incorporated into efficiency assessments through innovative DEA-based approaches. By explicitly modeling CO_2 emissions as an undesirable output, the analysis provides a transparent and data-driven way to evaluate hospitals' environmental responsibility. This contributes to a more systematic and comparable understanding of sustainability performance across hospitals.

By following the data-driven insights (peer benchmarks and slack targets), hospitals can devise focused improvement programs. Over time, such efforts should lead to more efficient and sustainable healthcare operations, ultimately benefiting not just the hospitals in terms of cost and performance metrics, but also the patients and communities they serve through better care and a healthier environment.

8. References

"ISO 9004:2018," ISO. Accessed: Nov. 27, 2024. [Online]. Available: https://www.iso.org/standard/70397.html

S. A. Almehwari, I. S. Almalki, B. A. Abumilha, and B. H. Altharwi, "Improving Hospital Efficiency and Cost Management: A Systematic Review and Meta-Analysis," Cureus, vol. 16, no. 10, p. e71721, doi: 10.7759/cureus.71721.

W. D. Cook and L. M. Seiford, "Data envelopment analysis (DEA) – Thirty years on," European Journal of Operational Research, vol. 192, no. 1, pp. 1–17, Jan. 2009, doi: 10.1016/j.ejor.2008.01.032.

M. Dolcini, F. Ferrè, A. Brambilla, and S. Capolongo, "Integrating environmental sustainability into hospitals performance management systems: a scoping review," BMC Health Services Research, vol. 25, no. 1, p. 764, May 2025, doi: 10.1186/s12913-025-12928-x.

B. Fang and M. Li, "Evaluation of healthcare efficiency in China: a three-stage data envelopment analysis of directional slacks-based measure," Front Public Health, vol. 12, p. 1393143, 2024, doi: 10.3389/fpubh.2024.1393143.

M. Ghahremanloo, A. Hasani, M. Amiri, M. Hashemi-Tabatabaei, M. Keshavarz-Ghorabaee, and L. Ustinovičius, "A novel DEA model for hospital performance evaluation based on the measurement of efficiency, effectiveness, and productivity," Engineering Management in Production and Services, vol. 12, no. 1, pp. 7–19, May 2020, doi: 10.2478/emj-2020-0001.

S. A. Hadian, R. Rezayatmand, S. Ketabi, N. Shaarbafchizadeh, and A. R. Pourghaderi, "Evaluating hospital performance with additive DEA and MPI: the Isfahan University of Medical Science case study," BMC Health Services Research, vol. 25, no. 1, p. 5, Jan. 2025, doi: 10.1186/s12913-024-12145-y.

F. F. Jahantigh and M. Ostovare, "Application of a hybrid method for performance evaluation of teaching hospitals in Tehran," Quality Management in Health Care, vol. 29, no. 4, pp. 210–217, 2020, doi: 10.1097/QMH.0000000000000265.

S. Jung, J. Son, C. Kim, and K. Chung, "Efficiency Measurement Using Data Envelopment Analysis (DEA) in Public Healthcare: Research Trends from 2017 to 2022," Processes, vol. 11, no. 3, Art. no. 3, Mar. 2023, doi: 10.3390/pr11030811.

K. Lennerts, Chapter 9: Facility management of hospitals in Book Investing in Hospitals of the Future. WHO Regional Office Europe, 2009.

F. Ma, W. Wang, Q. Sun, F. Liu, and X. Li, "Integrated Transport Efficiency and Its Spatial Convergence in China's Provinces: A Super-SBM DEA Model Considering Undesirable Outputs," Applied Sciences, vol. 8, no. 9, Art. no. 9, Sep. 2018, doi: 10.3390/app8091698.

J. Mirow, J. Venne, and A. Brand, "Green health: how to decarbonise global healthcare systems," Sustainable Earth Reviews, vol. 7, no. 1, p. 28, Oct. 2024, doi: 10.1186/s42055-024-00098-3.

A. Mitakos and P. Mpogiatzidis, "Adapting Efficiency Analysis in Health Systems: A Scoping Review of Data Envelopment Analysis Applications During the COVID-19 Pandemic," J Mark Access Health Policy, vol. 12, no. 4, pp. 306–316, Dec. 2024, doi: 10.3390/jmahp12040024.

A. Monzeli, B. Daneshian, G. Tohidi, and Sanei, "Improving Hospital Efficiency and Economic Performance: A DEA Approach with Undesirable Factors in Tehran Emergency Wards |

International Journal of Economic Sciences.” Accessed: Jun. 18, 2025. [Online]. Available: https://ijes-journal.org/journal/article/view/174

M. W. Moses et al., “Performance assessment of the county healthcare systems in Kenya: A mixed-methods analysis,” BMJ Global Health, vol. 6, no. 6, 2021, doi: 10.1136/bmjgh-2020-004707.

İ. Otay, B. Oztaysi, S. Cevik Onar, and C. Kahraman, “Multi-expert performance evaluation of healthcare institutions using an integrated intuitionistic fuzzy AHP&DEA methodology,” Knowledge-Based Systems, vol. 133, pp. 90–106, Oct. 2017, doi: 10.1016/j.knosys.2017.06.028.

M. G. M. Peixoto, M. A. Musetti, and M. C. A. Mendonça, “Multivariate analysis techniques applied for the performance measurement of Federal University Hospitals of Brazil,” Computers and Industrial Engineering, vol. 126, pp. 16–29, 2018, doi: 10.1016/j.cie.2018.09.020.

W.-J. Song, J.-W. Ren, C.-H. Chen, C.-X. Feng, L.-Q. Li, and C.-Y. Ma, “A Two-Stage Data Envelopment Analysis Approach Incorporating the Global Bounded Adjustment Measure to Evaluate the Efficiency of Medical Waste Recycling Systems with Undesirable Inputs and Outputs,” Sustainability, vol. 16, no. 10, Art. no. 10, Jan. 2024, doi: 10.3390/su16104023.

J. Yu, Z. Liu, T. Zhang, A. A. Hatab, and J. Lan, “Measuring productivity of healthcare services under environmental constraints: evidence from China,” BMC Health Serv Res, vol. 20, no. 1, p. 673, Jul. 2020, doi: 10.1186/s12913-020-05496-9.

W.-P. Wong, “A Global Search Method for Inputs and Outputs in Data Envelopment Analysis: Procedures and Managerial Perspectives,” Symmetry, vol. 13, no. 7, Art. no. 7, Jul. 2021, doi: 10.3390/sym13071155.

T. Żyłowski and J. Kozyra, “Crop Cultivation Efficiency and GHG Emission: SBM-DEA Model with Undesirable Output Approach,” Sustainability, vol. 15, no. 13, Art. no. 13, Jan. 2023, doi: 10.3390/su151310557.