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EFFICIENCY MEASUREMENT OF OECD HEALTH SYSTEMS USING OBJECTIVE WEIGHTING: AN INTEGRATED LOPCOW-DEA MODEL

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ABSTRACT

In this study, the relative efficiency of the health systems of Organisation for Economic Co-operation and Development (OECD) countries is evaluated through Data Envelopment Analysis (DEA) with an input-oriented variable returns scale (VRS) integrated with the Logic Objective Criteria Weighting (LOPCOW) method. In the study, five inputs (number of physicians (per 1000 people), number of beds (per 1000 people), health expenditure (per capita), number of MRI devices, and smoking) and three outputs (life expectancy, under-five mortality, and maternal mortality) were used. The LOPCOW method was utilized to obtain objective weights, which were integrated into the DEA model. The results indicate that 21 out of 34 OECD countries achieved full efficiency. The low efficiency scores of high-income countries such as Germany and Austria reveal that high health expenditures alone are not sufficient. Clusters of reference analyses show that the most representative countries are Israel, Chile, and Japan. Gap analysis indicates potential inefficiencies for resources and organizational. The findings indicate the need for reforms in health systems to enhance resource efficiency rather than merely increasing resource allocation. The model structure utilizing the objective weighting method offers a decision support mechanism for policymakers.

Keywords: operational research, efficiency, health

OECD ÜLKELERİNİN SAĞLIK SEKTÖRÜ ETKİNLİKLERİNİN İNCELENMESİ: LOPCOW-VZA ENTEGRE YÖNTEMİ

ÖZ

Bu çalışmada, OECD ülkelerinin sağlık sistemlerinin göreli etkinliği, Lojik Objektif Kriter Ağırlıklandırma (LOPCOW) yöntemi ile bütünleşik girdi yönelimli değişen getiri ölçekli (VRS) Veri Zarflama Analizi (VZA) aracılığıyla değerlendirilmiştir. Çalışmada, sağlık sistemi performansına ilişkin olarak beş girdi (hekim sayısı (1000 kişi başı), yatak sayısı (1000 kişi başı), sağlık harcaması (kişi başı), MRI cihazı sayısı, sigara kullanımı) ve üç çıktı (beklenen yaşam süresi, beş yaş altı ölüm oranı, anne ölüm oranı) kullanılmıştır. LOPCOW yöntemi ile ağırlıklandırılan değişkenler, teknik etkinlik analizine entegre edilmiştir. Elde edilen bulgular, 34 OECD ülkesinden 21'inin tam etkinlik düzeyinde olduğunu göstermektedir. Almanya ve Avusturya gibi yüksek gelirli ülkelerin düşük etkinlik skorları, yüksek sağlık harcamalarının tek başına yeterli olmadığını ortaya koymuştur. Referans küme analizleri, en çok örnek alınan ülkelerin İsrail, Şili ve Japonya olduğunu göstermiştir. Boşluk analizi sonuçları, bazı ülkelerde kaynak israfı ve organizasyonel verimsizliklere işaret etmektedir. Bu bulgular, sağlık sistemlerinde yalnızca kaynak artırımı yerine, kaynakların daha etkin kullanılmasına yönelik reformların gerekliliğini ortaya koymaktadır. Ayrıca, nesnel ağırlıklandırma yöntemi ile desteklenen model yapısı, politika yapıcılar için karar destek mekanizması oluşturabilecek niteliktedir.

Anahtar Kelimeler: yöneylem araştırması, etkinlik, sağlık

1. Introduction

OECD countries, which are a mix of developed and developing countries, display considerable differences in health system issues such as resource utilization efficiency, level of service delivery, and population access to health outcomes. Considering these differences, it is clear that it would be wrong to evaluate health services only through quantitative indicators without including efficiency. The extent to which these services are used efficiently should also be included in the analysis (OECD, 2023a).

The primary objective of this study is to reveal the relative efficiency of health systems by combining the LOPCOW, one of the criteria weighting methods under the category of decision-making methods, and the input-oriented VRS DEA, an efficiency analysis method. By integrating these two approaches, it is aimed to establish a highly discriminative model that is free from subjectivity.

In multi-criteria decision-making (MCDM) frameworks, various objective weighting methods are utilized to assess the relative significance of evaluation criteria. The Entropy, CRITIC, and LOPCOW methods are among the most commonly utilized approaches. The entropy method assesses the level of information dispersion or uncertainty associated with each criterion (Zou et al., 2006). The CRITIC method incorporates both contrast intensity and inter-criteria conflict through the integration of standard deviation and correlation coefficients (Diakoulaki et al., 1995). The LOPCOW method employs a logarithmic percentage transformation to effectively capture deviation-based logic and consistency, thereby achieving a balance between indicator discrimination and stability (Ecer & Pamucar, 2022; Dlouhý & Havlík, 2024). The ability to capture both variability and consensus, independent of subjective expert judgment, establishes it as a strong alternative for efficiency-oriented MCDM applications. The LOPCOW method independently determines the criteria weights objectively by using only the data set independent of decision-maker opinions; these weights are integrated into the DEA model through a normalization process, and the relative efficiency score of each country is calculated (Liang et al., 2006; Lukić, 2024).

In this study, the following input variables were used: number of physicians per thousand people, number of hospital beds per thousand people, health expenditure per capita, number of MRI devices, smoking rate; and life expectancy, under-five mortality rate, and maternal mortality rate as output variables. The selection of these variables was based on the comprehensiveness of the OECD statistical database and their relevance as demonstrated in similar studies found in the literature (Afonso & Aubyn, 2005; Gavurova et al., 2021; Joumard et al., 2010; Varabyova & Müller, 2016).

The findings to be found through efficiency analysis are intended to reveal in which areas countries' health systems perform relatively better and in which areas there is a need for improvement. This information will provide policymakers with important inputs for resource allocation, strategic planning, and performance evaluation.

The second section presents a comprehensive literature review, covering both the efficiency analysis of healthcare systems and the applications of the LOPCOW method. The third section describes the methodological framework, including the integration of the LOPCOW and DEA (VRS) models, variable selection, and data sources. The fourth section reports the empirical findings, including efficiency scores, reference sets, and gap analysis. The fifth section discusses the results in comparison with existing literature. The sixth section outlines policy and managerial implications, and the final section concludes the study by summarizing key contributions, limitations, and suggestions for future research.

2. Literature Review

This section presents a literature review on the LOPCOW method and the efficiency analysis of healthcare systems. This literature review analyzes the "Web of Science" and "Google Scholar" databases in relation to the LOPCOW method and the efficiency analysis of healthcare systems.

2.1. Efficiency Analysis in Healthcare Systems

The studies in the literature on the efficiency analysis of healthcare systems are given in Table 1.

TABLE 1 | Literature review for the efficiency of health systems

Author(s) and Year	Sample / Country / Year	Method(s) Used	Input Variables	Output Variables	Main Findings
Afonso & Aubyn (2005)	OECD countries, 2000	DEA, Free Disposal Hull	Doctors (per 1000 people), Nurses (per 1000 people), Hospital beds	Infant mortality, Life expectancy at birth	Many countries were found to be inefficient. Reference sets mainly include small country groups.
Asandului et al. (2014)	30 European countries, 2010	DEA	Doctors, Hospitals (per 1000 people), Beds (per 1000 people), GDP/Public Health Expenditure	Life expectancy, Healthy life years, Infant mortality	Some developed and developing countries lie on the efficiency frontier, the majority are inefficient.
Varabyova & Müller (2016)	22 country-level studies	Meta-analysis	Health expenditure, Doctors, Beds	Expenditure per health worker, Per capita expenditure	Efficiency scores are significantly affected by different datasets, methods, and models.
Gong et al. (2019)	30 Chinese provinces, 2009–2018	Dynamic Network DEA, Tobit regression	Health expenditure, Beds	Life expectancy, Maternal and Infant mortality	Efficiency in China showed a generally positive but fluctuating trend.
Ahmed et al. (2019)	46 Asian countries, 1995–2015	DEA	Health staff, Expenditure, Infrastructure indicators	Life expectancy, Maternal and Infant mortality	Large inter-country differences exist; low-efficiency countries may gain 30–40% through improvements.
Top et al. (2020)	36 African countries, 2017	DEA	Health staff, Financial resources, Infrastructure	Life expectancy, Mortality rates	Some low-income countries reached relatively high efficiency; no direct correlation between investment and efficiency.
Gavurova et al. (2021)	OECD countries, 2000–2008–2016	Dynamic Network DEA	Health expenditure, Education level, Spending types	Health outputs, Service quality, Efficiency scores	Overall efficiency declined; 19% improvement in public health subsystems, 8% in clinical services.
El Husseiny (2023)	20 Arab countries, 2010 and 2019	Two-stage DEA, Tobit	—	—	Potential efficiency gains varied between countries, up to 16% in some.
Dlouhý & Havlík (2024)	28 countries, 2018 data	MCDA + DEA	Health exp. (per capita), Doctors (per 1000 people), Infrastructure rate	Life expectancy, Infant mortality	Combining MCDA with DEA highlighted strong cross-country score differentiation.
Zeng et al. (2024)	China, 31 provinces, 2012–2021	DEA + Tobit regression	Health investment, Infrastructure, Staff	Patient services, Recovery rate	Human resource shortages identified as key issue in low-efficiency regions; incentive systems suggested.
Mitakos & Mpogiatzidis (2024)	Global cases, 2020–2023	DEA, Bootstrap DEA, Malmquist	Health staff, Hospital beds, Expenditure	Life expectancy, Infant mortality, Case outcomes	Interest in advanced DEA models rose post-COVID; such methods offer clearer policy implications.
Kergall & Mathonnat (2024)	Burkina Faso, 2017–2020	Bootstrap DEA	Expenditure, Health staff, Hospital beds	Patient number, Treatment time, Satisfaction	Bootstrap DEA confirmed systematic inefficiency; policy recommendations were made.
Hadian et al. (2025)	Iran, Isfahan Univ. Hospital, 2019–2022	Additive DEA, Malmquist Index, Super Efficiency	Health stations, Doctors (per 1000 people), Regional expenditure	Patient number, Service access, Quality index	Combining DEA models increased decision support accuracy; improvement areas were clearly identified.

Studies on analyzing the efficiency of health systems have gained popularity, especially in recently. In this respect, literature reviews have been conducted for various country groups as follows: OECD countries (Afonso & Aubyn, 2005; Gavurova et al., 2021), European countries (Asandului et al., 2014), Asian countries (Ahmed et al., 2019), Arab countries (El Husseiny, 2023), African countries (Top et al., 2020), and China (Gong et al., 2019; Zeng et al., 2024). Inputs such as health expenditures, healthcare personnel and infrastructure, and outputs such as life expectancy and mortality rates were generally used in the studies. The relative efficiency levels of the datasets were measured. The selection of input and output variables is not standardized and varies by study. Considering this situation, input and output variables were defined. These variables were selected by taking into account both the scope of the OECD database and their applicability in the previous literature so that the study is based on solid empirical foundations.

The literature summarized above shows that DEA and derivative methods are widely used in evaluating the performance of health systems.

First of all, many studies have used the classical DEA method. Although advanced techniques such as the Malmquist Productivity

Index, Bootstrap DEA, and Tobit regression have been shown to provide effective results in the existing literature (El Husseiny, 2023; Hadian et al., 2025; Kergall & Mathonnat, 2024), models integrating these methods in a comprehensive manner are not common enough. In particular, objective criteria weighting techniques such as LOPCOW seem to offer a significant advantage in terms of providing objective measurement by enabling decision-maker influence to be minimized; however, such models have a limited presence in the literature.

When the samples are analyzed, while OECD countries are frequently examined in the existing literature, most of these studies evaluate efficiency using a limited number of variables. When the study topics are analyzed, the structural transformation of health systems after COVID-19 has still been addressed in a limited number of studies; comprehensive analyses with up-to-date data sets, especially focusing on post-pandemic efficiency, are scarce (Mitakos & Mpogiatzidis, 2024). This situation reveals the need for more up-to-date, objectively weighted, and more multi-dimensional model-based analyses in OECD countries.

In light of these findings, this study proposes a DEA application integrated with LOPCOW, an up-to-date and objective weighting model. Hence, a data set that is free from decision-maker effects and has a high decomposition power will be generated. Therefore, the relative efficiency of health systems will be measured more precisely. Moreover, the use of up-to-date data sets and variable selection aims to fill both methodological gaps and empirical gaps in the literature.

2.2. Applications of the LOPCOW Method

The studies in the literature on the LOPCOW method are given in Table 2.

TABLE 2 | Literature review for LOPCOW Method

Author(s) and Year	Sample / Country / Year	Method(s) Used with LOPCOW	Subject
Bektaş (2022)	Turkish insurance sector, 2002–2021	MEREC, EDAS, CoCoSo	Performance evaluation of the Turkish insurance sector
Ecer & Pamucar (2022)	Turkish banks, 2020	DOBI	Sustainability performance assessment for Turkish banks
Kahreman & Kutlu (2023)	167 countries, 2022	PIV	Sustainable development performance
Keleş (2023)	G7+ Turkey, 2022	CRADIS	Performance assessment of livable powerhouse cities
Sumanto et al. (2023)	Indonesia, supply chain firms, 2022	SAW	Selection of waste treatment methods for food sources
Ulutaş et al. (2023)	Turkey, insulation materials	PSI, MEREC	Selecting the most efficient natural fiber for common commercial building insulation materials
Yaşar & Ünlü (2023)	8 Turkish universities, 2018–2022	MEREC, CoCoSo	Evaluation of sustainability in Turkish universities
Kahreman (2024)	Turkey, 2002–2020	CRADIS	Sustainable development and its subdimensions performance
Dhruva et al. (2025)	India (hypothetical data), no specific year	q-rung fuzzy data, COPRAS	Selection of waste treatment methods for food sources
Durdu (2025)	Firms listed in BIST sustainability index, Turkey	SPC, MARCOS	Evaluation of the financial performances of firms

The LOPCOW method, being comparatively new, was found in a limited number of studies throughout the literature research. The method was applied for criterion weighting across various subjects, such as insurance sector performance (Bektaş, 2022), sustainability performance (Ecer & Pamucar, 2022; Yaşar & Ünlü, 2023), sustainable development performance (Kahreman & Kutlu, 2023; Kahreman, 2024), performance of livable power center cities (Keleş, 2023), selection of waste treatment methods for food sources (Dhruva et al., 2025; Sumanto et al., 2023), optimal fiber cable selection (Ulutaş et al., 2023), and financial performance (Durdu, 2025). The method, despite being very new, provides more satisfying outcomes compared to existing criterion weighting methods (Ecer & Pamucar, 2022). This situation results from the elimination of significant differences between the criteria (Kahreman & Kutlu, 2023). The LOPCOW approach was selected as the criteria weighing technique in this study because of its newness and its comparative advantage over existing objective criterion weighting methods. Furthermore, the absence of the approach's application in health-related studies provides an additional reason for selecting it as the criterion weighting method.

3. Method

In this study, a two-stage method was applied to determine the relative efficiency levels of the health systems of OECD countries. In the first stage, the criteria weights are weighted by the LOPCOW method. In the second stage, these weights were integrated into an input-oriented VRS DEA model, and efficiency scores of health systems were determined.

3.1. LOPCOW Method

LOPCOW is an objective method for weighting criteria based on their discrimination power. In this method, standard deviations and logarithmic transformation values of the criteria are taken into account (Ecer & Pamucar, 2022). The LOPCOW method is inherently objective and does not necessitate subjective expert input; however, it is sensitive to the statistical structure of the input data, especially regarding inter-variable correlations. When input variables are highly correlated, it can lead to uneven weight distributions in the LOPCOW algorithm, making some indicators seem more important than they really are (Dlouhý & Havlík, 2024). This study analyzed a correlation matrix before the weighting process, revealing no significant multicollinearity ($|r| > 0.80$) (Golany & Roll, 1989). The derived weights have been considered methodologically acceptable, eliminating the need for dimensionality reduction techniques like a principal component analysis. Users of LOPCOW should check how the variables are related before processing to ensure that the final weight assignments are stable and distinct (Ecer & Pamucar, 2022).

In the first step, the decision matrix is created.

$$X=\left[x_{ij}\right] \qquad \left(i=1,2,\ldots,m;\ j=1,2,\ldots,n\right) \tag{1}$$

In the second step, matrix normalization values are calculated.

$$n_{ij}=\frac{x_{ij}}{m+\sum_{i=1}^{m}x_{ij}^{2}} \tag{2}$$

In the third step, preference values are calculated.

$$PV_i=\left|\frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(n_{ij}\right)^2}}{\ln\left(\frac{m}{\sigma}\right)}\right| \tag{3}$$

The weight for criterion i is

$$w_i=\frac{PV_i}{\sum_{j=1}^{n}PV_i} \tag{4}$$

3.2. DEA (VRS)

The criteria weights obtained by the LOPCOW method are integrated into the DEA model. The DEA model is input-oriented and aims to minimize inputs while maintaining a certain level of output. This model is also based on the VRS assumption.

The objective function of the relevant mathematical model is defined as follows:

$$min_{\theta,\lambda}\theta \tag{5}$$

Conditions:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_{xio} \quad \forall i \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad \forall r \tag{7}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{8}$$

$$\lambda_j \geq 0 \quad \forall j \tag{9}$$

Where:
θ: efficiency score; x, y: inputs and outputs; λ: intensity vector, o: the unit being evaluated.

In this model, inefficient decision units are compared with convex combinations of efficient units forming the reference set. Input orientation tests the feasibility of cost reduction-oriented policies. The VRS assumption provides flexibility to the production conditions of decision units of different scales (Seiford & Thrall, 1990).

3.3. LOPCOW-DEA Integration, Variable Selection and Data Sources

After the determination of the weights, weighting was applied with these weights. In the weighting process for the inputs, normalization was performed with the following formula.

$$x_{ij}^{*} = \frac{x_{ij} - \min\left(x_{.j}\right)}{\max\left(x_{.j}\right) - \min\left(x_{.j}\right)} \tag{10}$$

Where x_{ij}^{*} symbolized the normalized value.

After normalization, a weighted input value was calculated by dividing each input by the matching LOPCOW-derived weight, w_j^x .

$$x_{ij}^{norm} = x_{ij}^{*} x\, w_j^x \tag{11}$$

A similar method was also used to determine the weight of the output variables. First, the following formula was used to achieve normalization:

$$y_{ij}^{*} = \frac{y_{ij} - \min\left(y_{.j}\right)}{\max\left(y_{.j}\right) - \min\left(y_{.j}\right)} \tag{12}$$

Then, weighted outputs were computed as

$$y_{ij}^{*} = y_{ij}^{*} x\, w_j^y \tag{13}$$

Every variable contributes proportionately and objectively to the DEA model thanks to this normalization and weighting process, which eliminates decision-makers' bias.

3.4. Research Sample

Based on the availability of data, 34 OECD countries were included in the analysis. Data for Mexico and Costa Rica were inadequate, and Iceland and New Zealand were excluded because their life expectancy numbers were unavailable.

3.5. Research Instruments and Processes

The data used in the study were collected from three reliable sources: OECD Health Statistics (OECD, 2023b), Our World in Data (2023) and World Development Indicators (World Bank, 2023).

Table 3 shows the chosen input and output variables, their data sources, and the reference year (2021).

TABLE 3 | Input and output variables

Variable	Type	Unit	Source	Year	Code
Physicians (per 1000 people)	Input	Count	OECD	2021	INP1
Hospital beds (per 1000 people)	Input	Count	OECD	2021	INP2
Health expenditure (per capita)	Input	USD	World Bank	2021	INP3
Number of MRI machines	Input	Count	OECD	2021	INP4
Smoking prevalence (%)	Input	%	Our World in Data	2021	INP5
Life expectancy at birth	Output	Years	OECD	2021	OUT1
Under-five mortality rate	Output	per 1000	World Bank	2021	OUT2
Maternal mortality rate	Output	per 100000	World Bank	2021	OUT3

All the structural inputs at the resource level and the performance outcomes of health systems were intended to be expressed in the chosen variables. Every variable belongs to 2021 and was sourced from globally renowned and trustworthy data sources. The chosen indicators provide comparative cross-country analysis and are in line with the empirical research (Afonso & Aubyn, 2005; Ahmed et al., 2019).

The model's comparison validity improved, and consistency was guaranteed by selecting all variables from matched timeframes. In accordance with accepted methods in efficiency modeling, mortality-related indicators were reverse-coded, meaning that greater values denote better performance (Gong et al., 2019; Zeng et al., 2024).

3.6. Data Analysis

R was used to analyze the study's data, and correlation coefficients, LOPCOW, and input-ordered DEA (VRS) were applied.

4. Findings

First, a data matrix was created. In this data matrix, correlations between variables are analyzed. High correlation can weaken the discrimination ability of the model and reduce the reliability of efficiency scores. For this reason, it is not recommended to include highly correlated variables in the model (Bastani et al., 2021). Generally, it is recommended not to use variables together when the correlation coefficient |r|> 0.80 (Golany & Roll, 1989).

In this study, health sector data from OECD countries were used. Since all the necessary variables were available for only 34 of the 38 OECD countries, the analysis was limited to these 34 countries. Life expectancy at birth was not available for Iceland and New Zealand, and the values of all variables subject to analysis were not available for Mexico and Costa Rica. Data were obtained from three databases (OECD, 2023b; Our World in Data, 2023; World Bank, 2023).

The correlation matrix is given in Table 4.

TABLE 4 | Correlation matrix

Variables	INP1	INP2	INP3	INP4	INP5	OUT1	OUT2	OUT3
INP1	1.00	0.22	0.49	0.55	0.17	0.34	-0.42	-0.63
INP2	0.22	1.00	0.19	0.46	0.57	0.05	-0.15	-0.07
INP3	0.49	0.19	1.00	0.68	-0.25	0.70	-0.73	-0.60
INP4	0.55	0.46	0.68	1.00	-0.01	0.70	-0.72	-0.59
INP5	0.17	0.57	-0.25	-0.01	1.00	-0.34	0.40	0.07
OUT1	0.34	0.05	0.70	0.70	-0.34	1.00	-0.78	-0.65
OUT2	-0.42	-0.15	-0.73	-0.72	0.40	-0.78	1.00	0.67
OUT3	-0.63	-0.07	-0.60	-0.59	0.07	-0.65	0.67	1.00

According to the results of the analysis, the correlation values are between -0.78 and 0.70. No input or output variables were eliminated. Significant negative correlations are found between expenditure variables and under-five mortality and maternal mortality (ρ≈-0.56-0.73). These findings support the positive impact of health expenditure on outcomes. There are generally weak correlations between smoking rates and other variables. The number of hospital beds is weakly correlated with life expectancy at birth. In this study, weighted calculations are given separately for input and output variables within the scope of the LOPCOW method using health sector data from OECD countries.

Table 5 displays the normalized input variables.

TABLE 5 | Normalized input values

Country	INP1	INP2	INP3	INP4	INP5	Country	INP1	INP2	INP3	INP4	INP5
Germany	0.64	0.58	0.70	0.60	0.56	Italy	0.57	0.18	0.23	0.17	0.56
Australia	0.47	0.23	0.56	0.23	0.11	Japan	0.21	1.00	0.48	1.00	0.33
Austria	0.81	0.52	0.63	0.42	0.67	Colombia	0.11	0.03	0.00	0.04	0.17
Belgium	0.34	0.38	0.58	0.33	0.44	Costa Rica	0.00	0.00	0.04	0.00	0.00
Canada	0.28	0.12	0.67	0.14	0.17	Latvia	0.32	0.37	0.12	0.06	1.00
Czechia	0.51	0.46	0.29	0.17	0.61	Lithuania	0.43	0.41	0.15	0.08	0.89
Denmark	0.53	0.13	0.77	0.21	0.28	Luxembourg	0.32	0.33	0.77	0.14	0.44
Estonia	0.43	0.29	0.23	0.12	0.72	Hungary	0.38	0.50	0.19	0.12	0.72
Finland	0.36	0.21	0.53	0.19	0.33	Mexico	0.19	0.03	0.00	0.02	0.17
France	0.40	0.40	0.61	0.25	0.83	Norway	0.70	0.20	0.85	0.33	0.28
South Korea	0.19	0.92	0.34	0.67	0.44	Poland	0.19	0.45	0.23	0.14	0.83
Holland	0.45	0.19	0.66	0.17	0.39	Portugal	0.64	0.19	0.19	0.15	0.44
Ireland	0.34	0.15	0.58	0.14	0.50	Slovakia	0.40	0.40	0.16	0.10	0.78
Spain	0.53	0.16	0.34	0.21	0.61	Slovenia	0.32	0.29	0.22	0.12	0.56
Israel	0.36	0.15	0.29	0.10	0.44	Chile	0.11	0.08	0.12	0.06	0.33
Sweden	0.55	0.09	0.70	0.19	0.17	Türkiye	0.13	0.14	0.04	0.14	0.83
Switzerland	0.62	0.28	1.00	0.29	0.39	Greece	1.00	0.26	0.19	0.42	0.83

The normalization was used to rescale the values of the input variables to the [0,1] range.

Table 6 displays the PV scores.

TABLE 6 | PV values (Inputs)

Country	INP1	INP2	INP3	INP4	INP5	Country	INP1	INP2	INP3	INP4	INP5
Germany	0.06	0.07	0.08	0.07	0.04	Italy	0.04	0.03	0.03	0.02	0.04
Australia	0.04	0.03	0.06	0.03	0.01	Japan	0.04	0.10	0.06	0.09	0.04
Austria	0.07	0.06	0.07	0.06	0.05	Colombia	0.01	0.01	0.00	0.00	0.01
Belgium	0.04	0.05	0.05	0.04	0.03	Costa Rica	0.00	0.00	0.00	0.00	0.00
Canada	0.03	0.02	0.06	0.03	0.00	Latvia	0.03	0.04	0.00	0.02	0.07
Czechia	0.04	0.05	0.03	0.04	0.05	Lithuania	0.04	0.04	0.01	0.03	0.07
Denmark	0.05	0.03	0.07	0.04	0.01	Luxembourg	0.04	0.04	0.06	0.04	0.03
Estonia	0.04	0.04	0.02	0.02	0.05	Hungary	0.03	0.05	0.02	0.03	0.06
Finland	0.04	0.03	0.05	0.03	0.02	Mexico	0.01	0.01	0.00	0.00	0.01
France	0.05	0.05	0.05	0.04	0.06	Norway	0.06	0.04	0.09	0.05	0.02
South Korea	0.03	0.08	0.04	0.07	0.04	Poland	0.03	0.05	0.01	0.03	0.06
Holland	0.04	0.03	0.06	0.03	0.02	Portugal	0.04	0.03	0.03	0.02	0.04
Ireland	0.04	0.03	0.05	0.03	0.03	Slovakia	0.03	0.04	0.01	0.03	0.06
Spain	0.04	0.03	0.03	0.03	0.04	Slovenia	0.03	0.03	0.02	0.02	0.04
Israel	0.03	0.02	0.03	0.02	0.03	Chile	0.01	0.01	0.01	0.01	0.02
Sweden	0.05	0.02	0.07	0.03	0.01	Türkiye	0.02	0.03	-0.01	0.01	0.06
Switzerland	0.06	0.04	0.09	0.05	0.02	Greece	0.07	0.05	0.03	0.04	0.07

PV scores were calculated by multiplying the normalized input values by the variance-covariance matrix.

At the end, the weight values are displayed in Table 7 and were computed as follows.

TABLE 7 | Input weights

Variable	Weight
Physicians (per 1000)	0.1634
Hospital Beds (per 1000)	0.1814
Health Expenditure (USD)	0.2725
Number of MRI Units	0.1492
Smoking Prevalence (%)	0.2335

The table presents the objective weights derived from the PV scores of the input variables. Health Expenditure (USD) received the highest weight (27.25%), while Physicians per 1,000 Population and the Number of MRI Units received the lowest weights.

Appropriate transformations were used because certain output variables (such as mortality rates) are inversely oriented. Normalization and PV computations were then carried out.

Table 8 displays the normalized output values.

TABLE 8 | Normalized output values

Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3
Germany	0.67	0.85	0.93	Ireland	0.78	0.85	0.96	Hungary	0.17	0.70	0.82
Australia	0.89	0.90	0.95	Spain	0.91	0.87	0.98	Mexico	0.00	0.00	0.51
Austria	0.78	0.88	0.97	Israel	0.78	0.89	1.00	Norway	0.89	0.95	1.00
Belgium	0.72	0.89	0.94	Sweden	0.83	0.95	0.98	Poland	0.33	0.75	0.93
Canada	0.78	0.75	0.92	Switzerland	0.99	0.90	0.97	Portugal	0.67	0.90	0.92
Czechia	0.44	0.82	0.98	Italy	0.89	0.87	0.98	Slovakia	0.22	0.70	0.89
Denmark	0.67	0.90	0.97	Japan	1.00	1.00	0.97	Slovenia	0.67	0.85	0.95
Estonia	0.33	0.80	0.89	Colombia	0.22	0.70	0.00	Chile	0.56	0.70	0.84
Finland	0.72	0.92	0.99	Costa Rica	0.56	0.75	0.64	Türkiye	0.33	0.30	0.77
France	0.83	0.88	0.92	Latvia	0.00	0.60	0.80	Greece	0.67	0.85	1.00
South Korea	0.89	0.93	0.87	Lithuania	0.11	0.65	0.85				
Holland	0.78	0.90	0.95	Luxembourg	0.78	0.90	0.95				

By taking into account whether the output variables were cost- or benefit-oriented, they were normalized.

Table 9 displays the relevant PV scores.

TABLE 9 | PV values (Outputs)

Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3
Germany	0.12	0.08	0.07	Ireland	0.13	0.08	0.07	Hungary	0.07	0.05	0,05
Australia	0.14	0.09	0.08	Spain	0.14	0.09	0.08	Mexico	0.02	0.01	0,02
Austria	0.13	0.08	0.07	Israel	0.13	0.09	0.08	Norway	0.14	0.09	0,08
Belgium	0.13	0.08	0.07	Sweden	0.14	0.09	0.08	Poland	0.09	0.06	0,06
Canada	0.12	0.08	0.07	Switzerland	0.15	0.09	0.08	Portugal	0.12	0.08	0,07
Czechia	0.10	0.07	0.06	Italy	0.14	0.09	0.08	Slovakia	0.07	0.05	0,05
Denmark	0.12	0.08	0.07	Japan	0.15	0.10	0.08	Slovenia	0.12	0.08	0,07
Estonia	0.09	0.06	0.06	Colombia	0.05	0.04	0.02	Chile	0.10	0.07	0,06
Finland	0.13	0.08	0.07	Costa Rica	0.10	0.06	0.05	Türkiye	0.06	0.04	0,04
France	0.13	0.09	0.07	Latvia	0.05	0.04	0.04	Greece	0.12	0.08	0,07
South Korea	0.14	0.09	0.08	Lithuania	0.06	0.05	0.05				
Holland	0.13	0.08	0.07	Luxembourg	0.13	0.08	0.07				

The method's last step was figuring out the variable weights once the PV scores were calculated.

Table 10 displays the weights assigned to the output variables.

TABLE 10 | Output weights

Variable	Weights
Life Expectancy at Birth	0.5364
Under-Five Mortality Rate	0.2380
Maternal Mortality Rate	0.2256

Life expectancy at birth has the largest weight (53.64%) among the output variables. With slightly lower but balanced weights, the other two variables also contribute to the model.

A sensitivity analysis was conducted prior to the integration of the LOPCOW-generated weights into the DEA model to assess the robustness of the weighting structure. The objective was to figure out if minor adjustments in weight distribution could result in significant impacts on efficiency outcomes, thereby influencing the model's reliability. This type of robustness testing is frequently recommended in the MCDM literature for weight-based models (Saltelli et al., 2008; Triantaphyllou, 2000).

Table 11 provides a summary of five scenarios regarding input weights and three scenarios regarding output weights. Each scenario included uniform or targeted variations of weights, succeeded by renormalization. The chosen scenarios (±10% and ±15–20%) match earlier methods used in LOPCOW- or entropy-based decision research (Ecer & Pamucar, 2022).

TABLE 11 | Input and output LOPCOW weight scenarios

Scenario	Physicians	Beds	Health Expenditure (USD)	MRI Units	Smoking Rate (%)	Life Expectancy	Under-Five Mortality	Maternal Mortality
Original (Input)	0.1634	0.1814	0.2725	0.1492	0.2335	–	–	–
S1 Input (+10%)	0.1634	0.1814	0.2725	0.1492	0.2335	–	–	–
S2 Input (−10%)	0.1634	0.1814	0.2725	0.1492	0.2335	–	–	–
S3 Input (Health Exp. +20%)	0.1550	0.1720	0.3101	0.1415	0.2214	–	–	–
S4 Input (Beds & Smoking +15%)	0.1538	0.1964	0.2565	0.1405	0.2528	–	–	–
Original (Output)	–	–	–	–	–	0.5364	0.2380	0.2256
S3 Output (Life Exp. +20%)	–	–	–	–	–	0.5813	0.2149	0.2037
S4 Output (Mortality +15%)	–	–	–	–	–	0.5015	0.2559	0.2426

The sensitivity scenarios outlined above show that the LOPCOW-derived weights maintain consistent and balanced behavior in response to both uniform and targeted perturbations. The overall structure remains stable despite moderate changes in specific variable weights, ensuring the integrity of the DEA framework. The findings indicate that LOPCOW is methodologically compatible with DEA and offers a solid foundation for objective weight integration in efficiency measurement. The application of LOPCOW in DEA, especially within healthcare systems, is deemed valid and reliable.

The healthcare efficiency of 34 OECD countries was assessed using an input-oriented DEA model with VRS.

Table 12 displays the weighted input data matrix.

TABLE 12 | The weighted input data matrix

Country	INP1	INP2	INP3	INP4	INP5	Country	INP1	INP2	INP3	INP4	INP5
Germany	0.10	0.11	0.19	0.09	0.13	Italy	0.09	0.03	0.06	0.03	0.13
Australia	0.08	0.04	0.15	0.03	0.03	Japan	0.03	0.18	0.13	0.15	0.08
Austria	0.13	0.09	0.17	0.06	0.16	Colombia	0.02	0.01	0.00	0.01	0.04
Belgium	0.06	0.07	0.16	0.05	0.10	Costa Rica	0.00	0.00	0.01	0.00	0.00
Canada	0.05	0.02	0.18	0.02	0.04	Latvia	0.05	0.07	0.03	0.01	0.23
Czechia	0.08	0.08	0.08	0.03	0.14	Lithuania	0.07	0.07	0.04	0.01	0.21
Denmark	0.09	0.02	0.21	0.03	0.06	Luxembourg	0.05	0.06	0.21	0.02	0.10
Estonia	0.07	0.05	0.06	0.02	0.17	Hungary	0.06	0.09	0.05	0.02	0.17
Finland	0.06	0.04	0.14	0.03	0.08	Mexico	0.03	0.01	0.00	0.00	0.04
France	0.07	0.07	0.17	0.04	0.19	Norway	0.11	0.04	0.23	0.05	0.06
South Korea	0.03	0.17	0.09	0.10	0.10	Poland	0.03	0.08	0.06	0.02	0.19
Holland	0.07	0.03	0.18	0.03	0.09	Portugal	0.10	0.04	0.05	0.02	0.10
Ireland	0.06	0.03	0.16	0.02	0.12	Slovakia	0.07	0.07	0.04	0.01	0.18
Spain	0.09	0.03	0.09	0.03	0.14	Slovenia	0.05	0.05	0.06	0.02	0.13
Israel	0.06	0.03	0.08	0.01	0.10	Chile	0.02	0.01	0.03	0.01	0.08
Sweden	0.09	0.02	0.19	0.03	0.04	Türkiye	0.02	0.03	0.01	0.02	0.19
Switzerland	0.10	0.05	0.27	0.04	0.09	Greece	0.16	0.05	0.05	0.06	0.19

Table 13 displays the weighted output data matrix.

TABLE 13 | The weighted output data matrix

Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3	Country	OUT1	OUT2	OUT3
Germany	0.36	0.20	0.21	Ireland	0.42	0.20	0.22	Hungary	0.09	0.17	0.18
Australia	0.48	0.21	0.21	Spain	0.49	0.21	0.22	Mexico	0.00	0.00	0.11
Austria	0.42	0.21	0.22	Israel	0.42	0.21	0.23	Norway	0.48	0.23	0.23
Belgium	0.39	0.21	0.21	Sweden	0.45	0.23	0.22	Poland	0.18	0.18	0.21
Canada	0.42	0.18	0.21	Switzerland	0.53	0.21	0.22	Portugal	0.36	0.21	0.21
Czechia	0.24	0.20	0.22	Italy	0.48	0.21	0.22	Slovakia	0.12	0.17	0.20
Denmark	0.36	0.21	0.22	Japan	0.54	0.24	0.22	Slovenia	0.36	0.20	0.21
Estonia	0.18	0.19	0.20	Colombia	0.12	0.17	0.00	Chile	0.30	0.17	0.19
Finland	0.39	0.22	0.22	Costa Rica	0.30	0.18	0.14	Türkiye	0.18	0.07	0.17
France	0.45	0.21	0.21	Latvia	0.00	0.14	0.18	Greece	0.36	0.20	0.23
South Korea	0.48	0.22	0.20	Lithuania	0.06	0.15	0.19				
Holland	0.42	0.21	0.21	Luxembourg	0.42	0.21	0.21				

The input oriented VRS DEA model was employed subsequent to variable weighting. The results are displayed in Table 14.

TABLE 14 | Healthcare efficiency scores of OECD countries

Country	Efficiency Score	Country	Efficiency Score	Country	Efficiency Score
Australia	1.00	Germany	0.51	Norway	1.00
Austria	0.52	Greece	1.00	Poland	1.00
Belgium	0.82	Hungary	0.58	Portugal	1.00
Canada	1.00	Ireland	0.97	Slovakia	0.97
Chile	1.00	Israel	1.00	Slovenia	1.00
Colombia	1.00	Italy	1.00	South Korea	1.00
Costa Rica	1.00	Japan	1.00	Spain	1.00
Czechia	0.83	Latvia	0.88	Sweden	1.00
Denmark	0.86	Lithuania	0.89	Switzerland	1.00
Estonia	0.74	Luxembourg	1.00	Türkiye	1.00
Finland	1.00	Mexico	1.00		
France	0.90	Holland	0.85		

The OECD countries' relative healthcare efficiency scores are shown in Table 14. The DEA method, a non-parametric frontier technique, was used to compute these scores. A score of 1 means that a country's health system is entirely efficient, meaning it is generating the most output for the amount of input. Technical inefficiency is indicated by scores less than 1 (Jacobs et al., 2006).

Twenty-one of the thirty-four countries in Table 14 are totally efficient. This result implies that efficiency is influenced by both the amount of resources and how well those resources are converted into health outcomes (Kontodimopoulos et al., 2010).

Two developed economies are frequently thought to use similar strategies for their health systems. Austria (0.52) and Germany (0.51) have comparatively low efficiency scores. This result emphasizes that increased spending does not always convert to better health outcomes and that health financing does not always correspond with satisfactory performance.

Furthermore, countries with middling efficiency rankings include the Netherlands, Estonia, Belgium, and Czechia. By making small changes to their resource distribution, these countries might be able to achieve the efficiency frontier (Cylus et al., 2016).

This research indicates countries where fundamental health improvements should be given priority in addition to highlighting current performance levels. More accurate identification of areas where health systems might improve is made possible by DEA's gap analysis capabilities. The next part will go into more detail about these factors.

Reference sets for the inefficient countries were created at this point. Table 15 displays the reference sets.

TABLE 15 | Reference sets for inefficient countries

Country	Reference Sets	λ	Country	Reference Sets	λ	Country	Reference Sets	λ
Austria	Australia Costa Rica Israel	0.20 0.06 0.74	France	Australia Canada Israel Luxembourg	0.39 0.14 0.15 0.20	Lithuania	Türkiye Chile Italy	0.03 0.88 0.06
Belgium	Chile Costa Rica Israel Japan Luxembourg	0.03 0.12 0.62 0.20 0.03	Germany	South Korea Australia Costa Rica Israel	0.11 0.27 0.13 0.47	Holland	Slovenia Costa Rica Finland Israel Japan Luxembourg	0.06 0.08 0.07 0.55 0.03 0.02
Czechia	Chile Israel Italy Slovenia	0.04 0.33 0.40 0.23	Hungary	Japan Chile Costa Rica Greece	0.13 0.83 0.10 0.04	Slovakia	Sweden Chile Italy Slovenia	0.26 0.65 0.26 0.09
Denmark	Canada Chile Israel Sweden	0.12 0.05 0.23 0.61	Ireland	Türkiye Australia Canada Costa Rica Israel	0.03 0.08 0.25 0.05 0.62			
Estonia	Chile Costa Rica Israel Slovenia	0.26 0.12 0.03 0.58	Latvia	Japan Chile Costa Rica	0.01 0.81 0.16			

Table 15 shows that a reference set of efficient countries that form the production frontier and share similar features was selected for each inefficient country. All inefficient countries obtain their contributions from several reference units, according to an analysis of the reference connections. This result is consistent with the VRS assumption that reference points are usually created by convex combinations of several effective DMUs (Cooper et al., 2011).

Developing policy recommendations for inefficient countries may benefit from a structural analysis of the health systems of countries that are frequently cited. Israel is mentioned nine times, followed by Chile eight times, Costa Rica eight times, Japan six times, and Slovenia five times. Colombia, Greece, Mexico, Norway, Poland, Portugal, and Spain, on the other hand, were not included as references at all. Chile, Israel, and Italy were the countries with the largest total reference contributions.

These results show the importance of cross-national benchmarking in the formulation of health policy. More research should be done on countries that are commonly used as reference points to guide structural changes in ineffective systems. The literature supports this recommendation as well (Hollingsworth, 2008).

Figure 1 shows the spread of λ values for inefficient countries.

FIGURE 1 | Distribution of λ values by inefficient countries

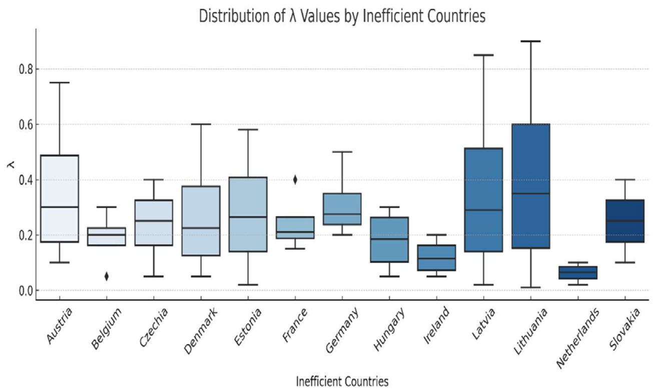

Figure 1 indicates the degree to which each reference unit contributes to the benchmarking of inefficient DMUs in the DEA model (Banker et al., 1984). In this context, λ values indicate the extent to which the performance of each inefficient country is bolstered by efficient peers that constitute the production frontier.

The boxplot illustrates the distribution, central tendency, and possible outliers within λ distributions. Latvia, Lithuania, and Austria demonstrate elevated median λ values and significant dispersion, reflecting their dependence on a limited number of dominant reference units. Latvia and Lithuania are often compared to Chile, whereas Austria's inefficiency is primarily addressed through comparison with Italy. The dependence on a restricted set of reference countries is termed reference concentration (Thanassoulis, 2001).

In contrast, Belgium, France, Ireland, and the Netherlands exhibit more compact λ distributions characterized by lower medians, indicating a more diversified or uniformly distributed benchmarking structure.

The variations highlight the diverse nature of inefficiency correction paths among OECD countries. Certain countries achieve efficiency by imitating a leading high-performing counterpart, whereas others gain advantages from a wider reference group. This distinction is essential for understanding country-specific reform strategies in health systems.

In DEA, input excesses and output shortfalls are used to identify the adjustments needed to make inefficient DMUs more efficient (Cooper et al., 2007). While output deficit shows the output that should have been attained given the current input levels, input excess is the amount of resource utilization that does not contribute to production.

Gap analysis measures the system's potential for development by comparing each DMU's present performance to its desired levels (Emrouznejad & Yang, 2018). After establishing the target values for inputs and outputs, the differences between the actual and desired values for each country were computed. The overall production shortfall and input excess for each country are presented in Table 16.

A gap analysis was carried out by computing the variations between the actual and target values for every nation once the input and output targets were established. The total output shortfalls and input excesses for all countries are shown in Table 16.

TABLE 16 | Gap analysis of OECD countries

Country	Total Input Excesses	Total Output Shortfalls	Country	Total Input Excesses	Total Output Shortfalls	Country	Total Input Excesses	Total Output Shortfalls
Australia	0.00	0.00	Germany	0.29	-0.08	Norway	0.00	0.00
Austria	0.24	0.00	Greece	0.00	0.00	Poland	0.00	0.00
Belgium	0.03	-0.04	Hungary	0.09	-0.21	Portugal	0.00	0.00
Canada	0.00	0.00	Ireland	-0.08	0.00	Slovakia	-0.14	-0.24
Chile	0.00	0.00	Israel	0.00	0.00	Slovenia	0.00	0.00
Colombia	0.00	0.00	Italy	0.00	0.00	South Korea	0.00	0.00
Costa Rica	0.00	0.00	Japan	0.00	0.00	Spain	0.00	0.00
Czechia	0.03	-0.19	Latvia	-0.17	-0.32	Sweden	0.00	0.00
Denmark	0.03	-0.07	Lithuania	-0.14	-0.27	Switzerland	0.00	0.00
Estonia	0.05	-0.16	Luxembourg	0.00	0.00	Türkiye	0.00	0.00
Finland	0.00	0.00	Mexico	0.00	0.00			
France	-0.07	-0.01	Holland	0.02	0.00			

The total input excesses and output shortfalls for each country are shown in Table 16. The slack variables derived from the DEA model were added together for this analysis.

Input excess and output shortage are zero in countries like Australia, Canada, Chile, Colombia, Costa Rica, Israel, Italy, Japan, South Korea, Spain, Sweden, Switzerland, Norway, Poland, Portugal, and Slovenia. These countries are regarded as totally efficient because they generate the greatest amount of output while making the most effective use of their inputs. According to the VRS assumption, such a situation is a sign of complete efficiency (Cooper et al., 2011).

By lowering their inputs while sustaining existing output levels, countries like Germany (0.29), Austria (0.24), Belgium (0.03), and Estonia (0.05) have the potential to become more efficient. These incidents demonstrate the wasteful use of medical resources (Charnes et al., 1978).

An inability to reach potential output is indicated by a negative output gap. With their present input levels, countries like Latvia (–0.32), Lithuania (–0.27), Hungary (–0.21), and Slovakia (–0.24) show the potential for improved health outcomes, but they are unable to do so because of structural or systemic inefficiencies.

Input slacks are negative in Latvia (–0.17), Lithuania (–0.14), Slovakia (–0.14), Ireland (–0.08), and France (–0.07). From a technical perspective, this means that the estimated target inputs are higher than the observed actual values. Such events, which are known in the literature as overfitting or model misspecification, may be caused by data normalization effects (Thanassoulis, 2001).

High input slack may indicate resource waste in countries like Germany and Austria. On the other hand, performance disparities in countries like Latvia and Lithuania, where production shortages prevail, may be caused by organizational inefficiencies, ineffective policies, or obstacles to access.

5. Discussion

This study's findings offer details about the relative efficiency of healthcare systems in OECD countries, demonstrating both consistency and divergence with existing studies. The use of an integrated LOPCOW–DEA (VRS) model provided a better assessment of performance by reducing subjectivity in variable weighting. This section mixes the current findings with prior empirical investigations and examines underlying patterns.

This study's principal finding is that 21 of the 34 OECD countries scored full efficiency, but countries with high health expenditures, including Germany and Austria, demonstrated comparatively low efficiency scores. This pattern supports the findings of Gavurova et al. (2021), who observed that financial resources alone are inadequate for attaining superior health outcomes. Joumard et al. (2010) similarly highlighted that structural and organizational elements frequently surpass basic expenditure levels in influencing system efficiency.

The comparatively low efficiency of wealthy economies such as Germany (0.51) and Austria (0.52) confirms the findings of Ahmed et al. (2019), which indicated that variations in health system efficiency among Asian countries were not directly related to economic prosperity but rather to the ability to convert inputs into successful outcomes. This study contributes to the existing literature by verifying that resource inefficiency persists in high-expenditure systems, suggesting possible managerial or structural deficiencies.

A significant observation is the presence of countries such as Israel, Chile, and Japan among the reference sets of inefficient units. This illustrates a phenomenon termed "reference concentration" by Thanassoulis (2001), wherein a limited number of structurally efficient DMUs function as shared benchmarks. The continuous citation of these countries across various inefficient DMUs indicates that they exhibit transferable best-practice characteristics deserving of further examination.

Furthermore, the gap study reveals considerable input surpluses in countries like Germany and Austria, with large output deficiencies in countries such as Latvia and Lithuania. The findings align with Zeng et al. (2024), who identified resource waste and structural obstacles as significant factors contributing to inefficiency in China's primary healthcare system. The existence of negative slacks in certain countries indicates either overfitting effects or significant organizational misalignments, a phenomenon previously seen by Emrouznejad and Yang (2018).

The integration of the LOPCOW method into DEA established a strong weighting framework. In contrast to other objective weighing systems like Entropy or CRITIC, LOPCOW improves discriminative capability by utilizing standard deviation and logarithmic preference values. This conclusion is consistent with the findings of Ecer and Pamucar (2022), who revealed that LOPCOW-based models exhibit enhanced sensitivity to data variability. This study validates these benefits within the framework of cross-national health system evaluation.

In conclusion, the findings of this study fit with the extensive literature on healthcare efficiency and show the imperative for policy reforms that extend beyond merely increasing financial resources. Organizational restructuring, equitable access, and health system governance are equally vital determinants of efficiency. These findings illustrate the practical importance of objective and integrated efficiency models for evidence-based policy development.

6. Policy and Managerial Implications

This study's findings are of vital significance for policymakers and healthcare professionals trying to improve system efficiency in OECD countries. The study uses an integrated LOPCOW–DEA method, beyond conventional input-output assessments that offers unbiased opinions about resource use and performance outcomes.

The comparatively low efficiency of countries like Germany and Austria, despite significant healthcare expenditure, underscores the necessity for policy reforms beyond merely enhancing financial resources. Policymakers in these countries ought to value resource reallocation, procedural optimization, and enhancement of preventive health programs. Performance-based budgeting, focused resource allocation, and the advancement of cost-effective methods should be prioritized.

The prominence of countries such as Israel, Chile, and Japan as reference benchmarks emphasizes the significance of cross-national policy learning. Healthcare managers ought to analyze exemplary practices from these effective systems—such as primary care coordination in Israel (Cylus et al., 2016), cost-efficient innovation in Japan (Joumard et al., 2010), and community-oriented health models in Chile (Frenz & Vega, 2010)—to guide structural reforms in underperforming countries.

The gap analysis offers practical insights for healthcare managers. Countries experiencing input excesses, such as Germany and Austria, ought to perform efficiency assessments to discover and eradicate unnecessary capacity. Meanwhile, countries experiencing production deficits (e.g., Latvia, Lithuania) need to invest in process optimization, employee training, and healthcare system accessibility.

The use of the LOPCOW technique shows the significance of objective performance assessment tools in management. In contrast to subjective weighting methods, LOPCOW-based systems function as decision-support instruments for assessing hospitals, departments, or regional systems, allowing managers to prioritize initiatives grounded in data-driven insights.

The model's capacity to detect resource waste and organizational inefficiencies underscores the necessity for governance change and performance monitoring. Health systems ought to implement adaptive management frameworks that integrate ongoing efficiency assessments, facilitating immediate policy modifications.

This study provides a methodology for comprehensive efficiency analysis that can inform both macro-level policy formulation and micro-level management strategies.

7. Conclusion

In this study, the relative effectiveness of health systems in OECD countries was investigated using the integrated LOPCOW-DEA model. According to the results, 21 of the 34 countries were determined to be on the efficiency frontier. This evidence suggests that by making the best use of their healthcare resources, these countries are able to produce their maximum amount.

The study's findings about the inefficiencies of wealthy, high-spending countries like Germany (0.51) and Austria (0.52) are among its most significant and interesting. This research shows that system success cannot be guaranteed by healthcare spending alone. It emphasizes that one of the main factors influencing health outcomes is the effective utilization of resources. Prior research by Gavurova et al. (2021) and Joumard et al. (2010), which prioritized structural efficiency over expenditure levels, reached similar findings.

It was found that the systems of Israel, Chile, and Japan—three of the model's most often mentioned reference countries—were, on average, more efficient and balanced. The majority of inefficient countries were found to be highly dependent on a small number of reference countries, according to reference set research. For instance, Italy served as Austria's primary reference country, whereas Chile made a substantial contribution to Latvia's and Lithuania's efficiency rankings. The literature refers to this phenomenon as "reference concentration" (Thanassoulis, 2001), and it frequently happens between structurally comparable countries.

However, countries with more uniform reference structures and smaller reference intensities included Germany, France, and Czechia. This conclusion implies that these countries' performance characteristics are similar to those of a larger peer group. Low reference diversity suggests that inefficient units have a higher chance of learning from certain national models.

The gap analysis's findings made the operational disparities in healthcare systems abundantly evident. For example, Austria (0.24) and Germany (0.29) had considerable input excess, suggesting that their systems may be wasteful of funds. However, countries such as Latvia (–0.32), Lithuania (–0.27), Hungary (–0.21), and Slovakia (–0.24) were shown to have notable output deficits, suggesting that their present levels of resources may result in significantly better health outcomes. These failures could be the result of weak governance, restricted access, or organizational inefficiencies (Banker et al., 1984).

The use of the LOPCOW approach is another significant contribution of this research. LOPCOW enhanced the DEA model's overall objectivity by allowing, based on data, objective criterion weighting that is not influenced by decision-maker bias. The novelty of this study is emphasized by the lack of such objectively weighted models in the literature. The discriminatory power of efficiency models in healthcare systems is improved by multi-criteria decision-making procedures, as highlighted by Dlouhý and Havlík (2024). The LOPCOW method is a structured approach for determining criterion weights based on performance deviations, but it has limitations. It operates on cross-sectional data and does not account for temporal dynamics, making it less useful in longitudinal analyses. Despite these limitations, LOPCOW remains a reliable alternative for objective MCDM weighting.

This study is subject to several limitations. The study utilized the most recent and comprehensive dataset for all variables, specifically from the year 2021, as the methodologies employed have their basis in cross-sectional data. Consequently, no time-series analysis was conducted, and the study fails to provide insights into the temporal changes in healthcare systems.

Secondly, some countries were excluded as DMUs due to insufficient data. This restriction reduced the overall sample size and may have constrained the applicability of the results.

The model employed in the study exclusively incorporates quantitative input and output variables for the evaluation of technical efficiency. Nonetheless, significant qualitative and subjective indicators—namely patient satisfaction, perceived service quality, access equity, provider responsiveness, and continuity of care—were omitted due to limitations in data availability. The variables are essential for comprehending system effectiveness from the user perspective and are increasingly highlighted in health system performance literature (Hadian et al., 2025)

Utilizing dynamic efficiency models to analyze performance variations over time and incorporating longitudinal data may allow future research to overcome these limitations. A more comprehensive evaluation could be attained by integrating subjective performance indicators that capture experiential quality, governance quality, digital health capabilities, and workforce satisfaction. Research on post-pandemic resilience, system adaptability, and recovery trajectories will provide significant insights into the changing health policy landscape.

Future research ought to examine the limitations of cross-sectional analysis by combining longitudinal datasets and utilizing dynamic efficiency models, such as the Malmquist DEA. This would facilitate the assessment of health system performance longitudinally and document alterations induced by reforms, demographic transitions, or crises such as pandemics.

Future studies should incorporate subjective and qualitative indicators, including patient satisfaction, perceived service quality, equity of access, continuity of care, and workforce morale, to achieve a comprehensive understanding of healthcare system effectiveness.

Additionally, analyzing post-pandemic resilience, digital transformation in healthcare delivery, and governance quality within health systems can offer substantial information about structural preparedness and adaptability. A hybrid approach that integrates objective efficiency scores with policy-sensitive qualitative dimensions might facilitate more actionable and comprehensive assessments.

In summary, this work uses an objective multi-criteria model enabled by LOPCOW to present a thorough and comparative efficiency analysis of OECD healthcare systems. The results provide a strategic framework for policymakers to establish priorities in addition to defining the performance environment as it exists today. In-depth analyses were carried out, including gap analysis and reference set evaluation, which guided policy transfer and gave information about cross-national learning. The findings make notable methodological and empirical contributions to the field of health economics and management, particularly by reinforcing practical recommendations on resource allocation and system restructuring.

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