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HEALTHCARE SYSTEM EFFICIENCY AND ITS DRIVERS IN PRE- AND COVID-19 PANDEMIC SETTINGS

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Purpose – The aim of the study is to assess healthcare system efficiency in both regular circumstances and during the COVID-19 pandemic, with a focus on key factors influencing efficiency, and offer health authorities insights into healthcare system resilience.

Research methodology – The analysis was conducted in two stages. The initial stage involved the application of Data Envelopment Analysis output-oriented model with a constant-return-to-scale framework. The second stage employed Tobit regression method to identify factors that influenced countries' efficiency.

Findings – We identified the healthcare system efficiency of 14 CIS and EU countries in Pre and pandemic settings and provided a methodology for results interpretation accounting for the complexity of healthcare systems and temporal variations in pandemic trends. The Tobit regression highlighted the role of the health workforce, emphasizing the caution for the reduction of physicians in the system.

Research limitations – The research focused on efficiency in just two regions of Eurasia and only considered medical factors as the primary drivers of efficiency. Additionally, the examination covered the initial year of the pandemic, reflecting only the earlier stages of countries' performance during the pandemic.

Practical implications – This study contributes to the assessment of healthcare resilience on a global scale and provides information for policymakers, aiding in the selection of optimal practices during the pandemic and enhancing preparedness for future crises.

Originality/Value – Countries' efficiency assessment in four models and two settings provides valuable insight into the healthcare systems' resilience.

Keywords: healthcare efficiency, health system resilience, health workforce, pandemic preparedness, DEA.

JEL Classification: I11, I15, I18.

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Introduction

Evaluating healthcare systems is crucial for improving their performance, strengthening their ability to face unexpected challenges, and learning from other countries to identify effective practices. These assessments play a vital role in refining healthcare policies and practices continuously, ultimately leading to better health outcomes for diverse populations.

While the COVID-19 pandemic is often described as a rare health crisis (World Health Organization, 2020a), it is essential to recognize that healthcare systems worldwide may encounter similar challenges in the future (OECD, 2023). Assessing healthcare efficiency during the pandemic and comparing it with regular circumstances provides valuable insights into how well the systems adapt and respond to sudden and significant challenges (OECD, 2023).

This process ensures the continuous delivery of essential services and minimizes the impact on public health. Evaluating healthcare system resilience involves examining their ability to respond to surges, allocate resources during crises, and implement effective emergency preparedness plans (OECD, 2023; Traore et al., 2023).

Cross-country comparisons of healthcare system efficiency are the most crucial step for advancing the understanding of healthcare system performance and readiness for future challenges. Evaluating the efficiency of healthcare systems is a complex endeavor due to its dependency on numerous factors (Bollyky et al., 2022; Kapitsinis, 2021). This challenge is attributed to the multidimensionality of healthcare systems that is the interaction of different part of the system together and with other country structures (Hradsky & Komarek, 2021; OECD, 2023). The efficiency assessment of the system during the pandemic represents the healthcare system response to unusual circumstances and depends on capacity healthcare system and a broader interaction with an infrastructure of the entire country that is linked to healthcare (Khan et al., 2019; Traore et al., 2023). Evaluation of healthcare efficiency is before and during the pandemic is the main step of assessment of resilience of healthcare systems that helps health authorities and policymakers to identified best practices during the pandemic and develop better resilience for the future crisis.

Analyzing prior literature on healthcare efficiency revealed several research gaps, mainly arising from the complexity of modeling healthcare systems (Panwar et al., 2022; Ratner et al., 2023) and variations in chosen indicators (Ratner et al., 2023; Zakowska & Godycki-Cwirko, 2019). The focus on high- and upper-middle-income countries limits insights into factors that affect efficiency in low and low-middle income countries (Mbau et al., 2022). Examining literature during the COVID-19 pandemic highlights challenges in country comparisons due to diversity among countries in pandemic developments and input/output selections, introducing bias and complexity in interpretation of results (Breitenbach et al., 2021b; Klumpp et al., 2022; Mourad et al., 2021; Ordu et al., 2021; Singh et al., 2023). Additionally, we found a lack of studies that examined efficiency incorporating the recommended metric of estimated excess death cases by the World Health Organization (WHO) for assessing the pandemic's impact (World Health Organization, 2023b).

Our study's aim is to assess healthcare systems efficiency in both regular circumstances and during the COVID-19 pandemic using the DEA method, with a focus on identifying key factors influencing efficiency and offering health authorities clear insights into healthcare system resilience for future crisis preparedness.

We tried to address the limitations in previous research by evaluating the efficiency of healthcare systems in 14 countries across Eastern Europe, Caucasus, and Central Asia. Our analysis unfolded in two stages. Initially, we applied the Data Envelopment Analysis (DEA) output-oriented model with a constant-return-to-scale framework. This allowed us to pinpoint healthcare system efficiency in both pre-pandemic and pandemic settings, and provided a methodology for results interpretation accounting for the complexity of healthcare systems and temporal variations in pandemic trends. We utilized estimated excess death cases related to COVID-19 for the outcome of the pandemic model, encompassing both direct and indirect pandemic impacts. The second stage involved employing the Tobit regression method to assess factors influencing healthcare efficiency in both settings. The disparities in efficiency between the two models and the varying effect of impact and directions of factors offer valuable insights into healthcare system resilience, identifying frontrunners in the region and, consequently, best practices during the COVID-19 pandemic. This information equips health authorities and policymakers with the tools to assess a country's healthcare system resilience and prepare for potential future crises.

1. Literature review

Healthcare system assessment is a fundamental aspect of future system development to ensure that it meets the diverse and dynamic health needs of populations (World Health Organization, 2022). By systematically assessing the performance of healthcare systems, policymakers and stakeholders can identify areas for improvement, allocate resources more effectively, and implement evidence-based interventions (Ozcan & Khushalani, 2017; World Health Organization, 2022). The cornerstone in this assessment is the identification of efficiency of the system and a cross-country comparison process.

Establishing efficiency in a healthcare system is intimately connected to the broader assessment of the system's performance. An efficient healthcare system ensures that resources are utilized judiciously, minimizing waste and maximizing the reach and impact of healthcare services (Boffardi, 2022; Hollingsworth & Peacock, 2008). The efficiency assessment methods can quantitatively measure the efficiency of different components of the healthcare system (Medeiros & Schwierz, 2015). These assessments provide valuable insights for scientists to identify areas for improvement, streamline processes, and ultimately enhance the overall effectiveness of the healthcare system (Arhin et al., 2023; Cylus et al., 2016; Evans & Etienne, 2010; Hollingsworth & Peacock, 2008; Kumbhakar, 2010).

Cross-country comparisons provide information about best practices and areas for improvement in healthcare systems. Comparative assessments allow to benchmark healthcare system's performance against other countries with different healthcare models (Mbau et al., 2022; Yetim et al., 2023). This facilitates the identification of successful strategies that may be applicable in different contexts, promoting knowledge exchange and fostering international collaboration (Herrera & Pang, 2005; Ibrahim, 2023; Kumbhakar, 2010; Ngami & Ventelou, 2023). Additionally, cross-country comparisons enable the identification of variations in health outcomes, healthcare access, and cost-effectiveness, offering a broader perspective on how different healthcare systems address common challenges (Hollingsworth & Peacock, 2008; Kumbhakar, 2010; Yetim et al., 2023).

The COVID-19 pandemic has significantly increased interest in cross-country analyses of healthcare system efficiency, given the unprecedented challenges it has presented globally (Bruinen de Bruin et al., 2020; World Health Organization, 2020a). Examining the disparities in efficiency among nations during the pandemic reveals crucial insights into the structural and operational factors influencing pandemic outcomes (Bollyky et al., 2022; Kapitsinis, 2021; OECD, 2023; Sorci et al., 2020). These differences reflect variations in capacities of healthcare systems, resource allocation approaches, and effectiveness of emergency responses during the crisis (Berchet et al., 2023; Bollyky et al., 2022; Dessie & Zewotir, 2021; Hradsky & Komarek, 2021). These factors collectively contribute to the resilience of healthcare systems, demonstrating their ability to effectively absorb, adapt, and respond to unforeseen and severe challenges (Iflaifel et al., 2020; OECD, 2023; Wiig et al., 2020). A thorough exploration of these aspects through systematic cross-country analyses enhances our understanding of healthcare system dynamics in the context of global health crises (Adabavazeh et al., 2023; Iflaifel et al., 2020).

One of the widely used approach for evaluating healthcare system efficiency is the DEA (Data Envelopment Analysis). The main advantage of DEA is the ability to conduct multi-dimensional analysis that allows the use of different categories of multiple inputs and outputs simultaneously, which is important for assessing the efficiency of complex healthcare systems (Behr & Theune, 2017). Moreover, the DEA technique could be customised to analyse different parts of healthcare systems (Kujawska, 2018; Ozcan & Khushalani, 2017; Sommersguter-Reichmann, 2022; Walters et al., 2022). As a result, it permits us to compare the efficiency of one healthcare system to another, rather than measuring efficiency in absolute terms and helps to establish benchmarking by identifying best practices and areas for improvement (Behr & Theune, 2017; Kujawska, 2018; Nyawira et al., 2021; Ozcan & Khushalani, 2017; Rostamzadeh et al., 2021; Vörösmarty & Dobos, 2023).

The flexibility of DEA is explained by the possibility of using different sets of measures for input and output to describe different parts of a healthcare system (Behr & Theune, 2017; Yari et al., 2023). The ideal input reflects all of the resources the healthcare system uses to improve the population's health status – output (Afonso & St. Aubyn, 2006; Behr & Theune, 2017). Inputs are the resources and/or factors that a decision-making unit (DMU) needs to achieve its objectives efficiently (Afonso & St. Aubyn, 2006; Spinks & Hollingsworth, 2009; Zakowska & Godycki-Cwirko, 2019). Outputs represent the outcomes, products, or services produced or delivered by a DMU as a result of using its inputs (Afonso & St. Aubyn, 2006; Medeiros & Schwierz, 2015; Spinks & Hollingsworth, 2009; Zakowska & Godycki-Cwirko, 2019).

While the DEA model can incorporate diverse inputs to capture the multifaceted nature of healthcare systems, it falls short in comprehensively representing all the elements that impact system output. As a result, researchers use set of variables that varies dramatically and surrogate measures to approximate these influential factors (Mitropoulos, 2021; Ozcan & Khushalani, 2017; Timofeyev et al., 2023). These introduces subjectivity and potential for biases and uncertainty in the analysis, leading to divergent results and varying opinions interpretations of a study results (Panwar et al., 2022; Ratner et al., 2023).

Several publications, including Mourad et al. (2021), Ordu et al. (2021), Breitenbach et al. (2021b), Klumpp et al. (2022) and Singh et al. (2023) examined countries efficiency during the COVID-19 pandemic. Thus, Ordu et al. (2021) presented findings from 16 countries using DEA, focusing on a 5-week period after identifying the first 100 COVID-19 cases in each country. A distinctive aspect was excluding the initial 100 cases to adjust for variations in epidemic wave timings among countries, although this adjustment didn't fully capture regional differences in pandemic dynamics. Notably, raw counts, not rates, were used for COVID-19 cases and deaths. A similar methodological approach was used in another study by Klumpp et al. (2022), analyzing healthcare efficiency impact across 19 OECD countries over 12 time periods, starting from the first COVID-19 death in each country. The primary focus was comparing the effects of restriction policies during the initial wave of the pandemic.

Mourad et al. (2021) assessed healthcare system efficiency during the initial phase of the COVID-19 pandemic across 29 countries. Using input variables like confirmed cases and medical resources, and output variables such as recovered and deceased cases, the study identified China, India, and Pakistan as having the most efficient systems, with France ranked the least efficient. However, reliability concerns exist due to unclear rationale for variable selection and diverse epidemic trends. Similar issues were found in another study (Breitenbach et al., 2021a). The data were collected 100 days from the first confirmed COVID-19 case in Wuhan that also ignored countries differences in epidemic development. Despite methodological considerations, these findings align to some extent with prior research (Mourad et al., 2021).

Lupu and Tiganasu (2022) utilized Data Envelopment Analysis (DEA) to assess healthcare system performance during the COVID-19 pandemic across thirty-one European countries. The study spanned the pandemic's first year, dividing into the first wave (January 1 to June 15), the relaxation phase (June 15 to October 1), and the second wave (October 1 to December 31). The chosen timeframes align with reported death counts in the European Union, however, many EU countries had distinct epidemic trends. Such variations in trends could introduce bias. Notably, the study used the total number of reported COVID-19 death cases as an output variable, but other variables were presented as proportions (Lupu & Tiganasu, 2022).

Keskin and Delice (2023) proposed an innovative, multi-dimensional efficiency approach for assessing OECD countries' COVID-19 response, integrating various techniques like DEA. However, the complexity of their analysis may challenge result interpretation, particularly for policymakers not familiar with the method. In another study, Kuzior et al. (2022) categorized healthcare systems and found the Beveridge model performed the best, followed by the Bismarck and National Insurance models, while the Market model demonstrated the poorest resilience to the pandemic. However, clarity was lacking on data collection duration and specific COVID-related variables employed.

Examining previous studies on healthcare efficiency using DEA reveals several gaps in the scientific literature. The primary challenge lies in modeling complex systems like healthcare, leading to differences in assessed models and study outcomes (Panwar et al., 2022; Ratner et al., 2023). This discrepancy often stems from the varied choice of indicators representing inputs, intermediates, and outputs of the healthcare system (Ratner et al., 2023; Zakowska & Godycki-Cwirko, 2019). The lack of universally accepted indicators is a major problem. Additionally, most research focuses on high- and upper-middle-income countries, limiting insights into the factors driving efficiency in low and low-middle income countries (Mbau et al., 2022). Assessing literature on healthcare system efficiency in the context of the COVID-19 pandemic showed the main obstacles in countries comparison were different variations of the pandemic development in countries and diversity in selecting inputs and outputs (Breitenbach et al., 2021b; Klumpp et al., 2022; Mourad et al., 2021; Ordu et al., 2021; Singh et al., 2023). Both of these bias the results and bring complexity in results interpretation. Furthermore, we found no DEA studies incorporating estimated excess death cases related to the COVID-19 pandemic (Wang et al., 2022), a metric recommended by the World Health Organization (WHO) for assessing the pandemic's impact (World Health Organization, 2023b).

2. Methods

Our research comprises data from 14 countries. The data were collected from different sources. The health-related data and data pertaining to the COVID-19 pandemic were collected from the World Health Organization, and socio-economic indicators were taken from the World Bank database. The COVID-related data spans the period of the first pandemic year – 2020, while other non-COVID data is from the prior to the pandemic year – 2019. In instances where 2019 data was not available, we substituted it with the closest preceding year's data or retrieved it from alternative sources. An overview of the data sources utilized in our study can be seen in Table 1.

Our selection of countries included countries that formed the Commonwealth of Independent States (CIS), a regional organization of post-Soviet states, and countries of Eastern Europe. Our choice of countries covered regions of Central Asia, the Caucasus, and Eastern Europe. The analysis of healthcare efficiency in CIS countries is relatively scarce and we decided to address this limitation. Furthermore, we incorporated Eastern European countries that were either part of the former Soviet Union or were influenced by it. Notably, the healthcare systems in these nations exhibit many commonalities and have undergone significant transformations since the collapse of the Soviet Union.

Table 1. The list of variables used in the analysis

Variables used in DEA analysis	Definition	The source of variables
Input variables used in DEA analysis		
Physicians	Medical doctors per 10.000 population in 2019	World Health Organization (2023c), Pan American Health Organization (2023)
Nurses	Nurses per 10.000 population in 2019	World Health Organization (2023d), Pan American Health Organization (2023)
Hospital beds	Hospital beds per 10.000 population in 2019	World Health Organization (2020c), Pan American Health Organization (2023)
Life expectancy	Life expectancy over 15 years old in 2019	World Health Organization (2020d)
Health expenditure per GDP	Health expenditure per capita / Gross domestic product per capita in 2019	World Health Organization (2023a)
Output variables used in DEA analysis		
Healthy life expectancy at birth	The average number of years in full health a person after birth can expect to live based on current rates of ill-health and mortality.	(World Health Organization, 2020b)
Healthy life expectancy at age 60 (years)	The average number of years in full health a person at age 60 can expect to live based on current rates of ill-health and mortality.	(World Health Organization, 2020e.)
Age-specific death excess rate	Estimated excess death cases associated with the COVID-19 pandemic in 2020 and 2021 / Country population 15 and older in 2019 per 10.000 population	World Health Organization (2023b)

Our analysis was conducted in two distinct stages. The initial stage involved the application of Data Envelopment Analysis (DEA). Within this stage, we employed several models to characterize and compare the different states of healthcare systems. The first three models, denoted as Models A, B, and C, provided descriptions of healthcare systems under typical conditions before the onset of the COVID-19 pandemic. Model A, serving as the base model, integrated the outcomes of Models B and C to provide a comprehensive viewpoint. Models B and C, in turn, delved into specific components, providing detailed insights into the factors contributing to Model A.

The distinguishing feature among the first three models lies in the selection of the output variable. Model A incorporated Health-Adjusted Life Expectancy (HALE) at birth and HALE at age 60 as output variables. In contrast, the other two models centered around a single output variable, each designed to assess healthcare system performance by distinct measures. Specifically, Model B employed HALE at birth as the output variable, while Model C focused on HALE at age 60.

In contrast, the last model, Model D, focused on evaluating healthcare system performance during the initial year of the pandemic, a period marked by crisis

The subsequent stage of our analysis aimed to ascertain the impact of input variables on the efficiency of healthcare systems achieved through the utilization of Tobit regression. In these regression models, the dependent variable was the efficiency of Models A and D, allowing us to gain insights into how various input factors influenced the efficiency of these healthcare systems before and during the crisis. The differences in effect of variables on the efficiency of the healthcare systems in two settings provided valuable information about healthcare resilience during the pandemic.

To explore the variability of the variables utilized in our analysis, we calculated the means and confidence intervals for each variable to provide a summary of their central tendencies and the range of values they encompass (Table 2). Furthermore, we conducted t-tests to compare differences in these variables between two distinct groups: countries within the European Union (EU) and countries within the Commonwealth of Independent States (CIS). This comparative analysis allowed us to assess the disparities and similarities in these two groups.

The selection of input variables for the Data Envelopment Analysis (DEA) encompasses three distinct sets of variables (Table 1). The first set described aspects of medical care, including the healthcare workforce, such as physicians and nurses, as well as the availability of hospital beds. Additionally, it incorporates econometric variable, such as health expenditure as a proportion to GDP and life expectancy, which serves as an important measure accentuating disparities within the public health sector across countries.

The output variables for the DEA comprised of Health-Adjusted Life Expectancy (HALE) measures that inherently capture the culmination of a healthcare system's efforts. The core model (Model A) constituted the combination of HALE measures such as HALE at birth and HALE at age 60. The other two models (Model B and C) investigated these HALE measures separately, allowing for a more nuanced assessment of healthcare system performance.

In the context of the DEA analysis during the initial year of the pandemic (Model D), the output revolves around a single metric – the rate of estimated excess death linked to the COVID-19 pandemic for the years 2020. This specific measure of estimated excess death cases related to the COVID-19 pandemic has been introduced by the World Health Organization (Wang et al., 2022; World Health Organization, 2023b). This measure addresses a notable limitation observed in the common practice – COVID-19 reported death, which often underestimated the true extent of lives lost due to the pandemic.

To obtain our results, we employed an output-oriented model with a constant-return-to-scale (CRS) framework. Within the CRS scale, the dimensions of output are considered to change in proportion to variations in input quantities (Barpanda & Sreekumar, 2020). This particular model orientation enables us to assess whether a Decision-Making Unit (DMU) has the potential to enhance its outputs while maintaining the inputs at a constant level, as discussed by Skica et al. (2019). The core equations that define the CRS output-oriented model are provided below:

$$\text{Minimize} \sum_{i=1} \nu_i x_{ik};$$

$$s.t. \quad \sum_{i=1}^{m} \nu_i x_{ik} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \qquad j = 1,\ldots,n;$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1;$$

$$u_r, \nu_i > 0 \qquad \forall r = 1,\ldots,s; i = 1,\ldots,m,$$

where: y_{rk} – quantity of output r produced by country k; x_{ik} – quantity of input i covered by country k; u_r – the weights of output r; ν_i – the weights of input i; n – number of countries to be evaluated; s – number of outputs; m – number of inputs.

It is essential to recognize that the dependent variable, technical efficiency, exists within the bounds of 0 and 1. To ensure the accuracy of our parameter estimates and mitigate bias, we opted for the use of censored Tobit regression models, in line with the pioneering work of Tobit in Tobit (1958), Mok et al. (2007).

$$y_i^* = x_i \beta + \varepsilon_i;$$

$$y_i = \begin{cases} 0 \; if \; y_i^* \leq 0 \\ y_i^* \; if \; 0 < y_i^* < 1, \\ 1 \; if \; y_i^* \geq 1 \end{cases}$$

i = 1,…,N – indicates the observation; y_i^* – an unobserved ("latent") variable; x_i – is a vector of explanatory variables; β – is a vector of unknown parameters; ε_i – is a disturbance term.

Two Tobit regression models were calculated using variables and efficiency results from Model A and D.

The data management was performed on SAS 9.04 software (SAS Institute). Descriptive statistics, DEA, and Tobit regression were conducted using STATA 17. A statistical significance level of 0.05 was applied.

3. Results

The descriptive statistics for the variables in the final analytical sample of countries are detailed in Table 2. Additionally, we conducted a comparative assessment of model variables between countries in the Commonwealth of Independent States (CIS) and the European Union (EU). Statistically significant differences emerged within these groups in variables Health-Adjusted Life Expectancy (HALE) at birth and HALE at age 60 ($t = –4.2966$, $p = 0.0010$; $t = –3.6893$, $p = 0.0031$, respectively). However, the input variables displayed no statistical differences, with the exception of Health Expenditure ($t = –5.8861$, $p = 0.0001$).

Table 2. Descriptive statistics of variables used in the analysis

Variables	Mean	95% CI
Physicians (medical doctors)	34.36529	[28.65, 40.08]
Nurses	69.67393	[56.60, 82.75]
Hospital beds	59.37857	[49.59, 69.16]
Health expenditure per capita	789.0136	[441.78, 1136.25]
Life expectancy	61.09571	[59.83, 62.36]
Healthy life expectancy at birth	66.29286	[65.09, 67.50]
Healthy life expectancy at age 60	15.40714	[14.68, 16.14]
Age-specific death excess	0.9980539	[0.9975, 0.9986]

The findings from the Data Envelopment Analysis (DEA) of four distinct models are showed in Table 3. Model A, as the foundational model, consolidated the results of Models B and C, providing a holistic perspective. The subsequent models, Models B and C, offered detailed insights into the components contributing to Model A. On the contrary, Model D assessed the efficiency during the initial year of the COVID-19 pandemic. A comparative examination between Model A and Model C illuminates the differences in healthcare system functionality under regular circumstances and during the pandemic, contributing valuable insights into the impact of this unprecedented event on healthcare system efficiency.

The most efficient countries in our analytical dataset were Kyrgyzstan and Moldova, consistently securing the top rank in all four models. On the other end of the efficiency spectrum, Belarus and Czechia exhibited the lowest performance, with efficiency scores of 0.408 and 0.609, respectively, in Model A. Both countries displayed slightly reduced efficiency in Model C when compared to Model B (0.408 vs. 0.398 for Belarus and 0.609 vs. 0.604 for Czechia). However, Belarus experienced a significant surge in performance during the first year of the COVID-19 pandemic, increasing the rank to the 8th position with an efficiency score of 0.947 (Model c). In contrast, Czechia became the least efficient country in the set during the pandemic, ranking 14th with an efficiency score of 0.885.

The disparity between Models B and C unveiled two types of trends. While the majority of countries demonstrated higher efficiency scores in Model B compared to Model C, there were exceptions. Countries like Latvia, Estonia, Poland, Slovakia, and Bulgaria exhibited a reverse pattern. Intriguingly, those countries with a reverse pattern and an efficiency score difference exceeding 2% showed lower efficiency ranks during the COVID-19 pandemic compared to the preceding models, adding an interesting layer to the understanding of healthcare system performance under pandemic conditions.

Table 3. The cross-country efficiency by models (The results of DEA analysis)

Country	Model A		Model B		Model C		Model D	
	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency
Azerbaijan	7	0.882052	7	0.882052	9	0.785916	4	0.996424
Belarus	14	0.408336	14	0.408336	14	0.397065	8	0.947274
Kazakhstan	10	0.725684	10	0.725684	11	0.692504	7	0.951914
Kyrgyzstan	1	1	1	1	1	1	1	1
Moldova	1	1	1	1	1	1	1	1
Tajikistan	3	0.947208	3	0.947208	8	0.813175	1	1
Latvia	5	0.92967	5	0.906682	4	0.92967	5	0.967345
Lithuania	12	0.635261	12	0.632698	12	0.635261	10	0.928521
Estonia	6	0.929205	6	0.88684	5	0.929205	11	0.917864
Poland	4	0.9451	4	0.922144	3	0.9451	13	0.900903
Romania	11	0.71569	11	0.71569	10	0.704999	9	0.932267
Slovakia	9	0.837859	9	0.806616	7	0.837859	12	0.904292
Czechia	13	0.608717	13	0.608717	13	0.604647	14	0.885911
Bulgaria	8	0.855647	8	0.844807	6	0.855647	6	0.965894

Thus, Poland experienced a decline from the 4th position in the efficiency ranking, with a score of 0.945, to the 13th rank, accompanied by an efficiency score of 0.901. Similarly, Estonia descended from the 6th rank with an efficiency score of 0.929 to the 11th position with the same efficiency score. The inherent nature of outputs in Model A and D differs, precluding a direct comparison of efficiency scores between these models. Instead, our focus lies on the countries' ranks within the analytical countries sample.

Countries that exhibited significant increase in their performance ranking during the COVID-19 pandemic included Belarus, Azerbaijan, and Tajikistan. Belarus, for instance, ascended from the 14th position in the ranking with an efficiency score of 0.408, to an impressive 8th place, achieving an efficiency score of 0.947. These notable improvements underscore the dynamic nature of healthcare system performance during the pandemic, with certain countries demonstrating considerable adaptability and efficacy in response to the unprecedented challenges posed by the COVID-19 crisis.

To assess the impact of various factors on cross-country efficiency in Models A and D, Tobit regression analysis was conducted, and the results are detailed in Table 4. Within the first model for all countries, input variables exhibited negative coefficients, with the exception of Health Expenditure, which, however, did not emerge as a statistically significant predictor. The other variables in the model demonstrated statistical significance, with the Physicians exerting the most substantial influence on the country efficiency, indicated by a coefficient of (–0.008).

Examination of regression for Model D for all countries showed that variables such as Nurses, Hospital Beds, and Health Expenditure retained negative coefficients and remained statistically significant predictors. In contrast, Physicians experienced a change in the sign of

Table 4. Influence of factors on the cross-country efficiency (The results of Tobit regression)

Variables	Model A			Model D		
	All countries *Coefficient SE*	CIS countries *Coefficient SE*	EU countries *Coefficient SE*	All countries Coefficient SE	CIS countries *Coefficient SE*	EU countries *Coefficient SE*
Intercept	1.4340* 0.0600	1.4096* 0.0079	1.6577* 0.0728	1.4116* 0.1479	1.0981* 0.0001	1.4634* 0.3057
Physicians	–0.0077* 0.0025	–0.0099 * 0.0009	–0.0024 0.0015	0.0008 0.0005	0.0005* 0.0000	0.0008 0.0011
Nurses	–0.0034* 0.0009	–0.0022* 0.0003	–0.0013 0.0006	–0.0007* 0.0002	–0.0010* 0.0000	0.0006 0.0004
Hospital beds	–0.0019 0.0014	–0.0030* 0.0002	–0.0050* 0.0013	–0.0003 0.0002	0.0004* 0.0000	–0.0023 0.0009
Health expenditure	0.0001 0.0000	0.0003* 0.0000	–0.0002* 0.0000	–0.0001* 0.00001	–0.0001* 0.0000	–0.0001 0.0000
Life expectancy				–0.0064* 0.0025	–0.0011* 0.0000	–0.0050 0.0051
Log Likelihood	20.7858	22.3221	20.7047	45.4358	185.4489	24.6418
Pseudo R^{2+}	–3.0503	24.6639	–1.3438	–0.7629	–12.2338	–0.3080

Note: * statistically significant coefficient.

their coefficients. Specifically, the effect of Health Expenditure turned negative (–0.0001) and attained statistical significance, while the variable Physicians retained its status as the most influential factor but exhibited a change in the coefficient's sign (0.0008). This shift in the coefficient of physicians may suggest a reverse effect of physician rate during the COVID-19 pandemic, highlighting the dynamic nature of the factors influencing healthcare system efficiency under pandemic conditions.

To further examine the impact of the medical set of variables on country efficiency Tobit regression was separately conducted for two distinct groups of countries, CIS and the EU, for Models A and D. The results of separate DEA for these groups were presented in Appendix.

In Model A for CIS and EU countries, all variables exhibited consistent directional trends for both groups similar to the previous analysis of all countries in the data set, except Health Expenditure in EU group (Table 4). However, for CIS countries in Model A, the most influential and statistically significant factor was Physicians (–0.010), whereas for the EU, it was Hospital Beds (–0.005). Considering Model D for CIS and EU countries, similar trends were observed for both groups compared to the main data set. Thus, the coefficients for Physicians in the CIS and EU groups remained positive values (0.0005 and 0.0008, respectively), but the coefficients for Hospital Beds in CIS group and Nurses in EU group for the Model D demonstrated a positive direction (0.0004 and 0.0006, respectively), although Nurses did not attain statistical significance. Remarkably, Nurses in CIS group and Hospital Beds in EU group exhibited as the most influential factor, characterized by a coefficient of (–0.001, 0.002, respectively), emphasizing its prominent role in influencing country efficiency during the pandemic.

4. Discussion

The main objectives of our study were: first, to evaluate the healthcare systems efficiency of countries before and during the COVID-19 pandemic by employing the DEA method, second, to identify main factors that influence countries system efficiency using Tobit regression, and, finally, to provide health authorities with comprehensible insights into the performance of each healthcare system.

It is necessary to consider several critical factors while interpreting a country's efficiency in our analysis. These critical considerations are complexity and interactive nature of factors influencing healthcare system performance, the distinctive temporal variations in COVID-19 pandemic trends across countries, and the inherent limitations of the DEA method employed for the analysis.

The complexity of any healthcare system introduces dimensionality, encompassing variations in the performance of its individual units, and interdependency, representing the system's interaction with larger societal structures within the country. This complexity underscores the need to control for numerous factors when conducting cross-country comparisons. To address these complexities, we recommend adjusting the interpretation of results of DEA by comparing country efficiency within small groups, such as among CIS or EU countries, or specific regional subsets like the Baltic states or Central Asia countries. This approach enables a more accurate comparison, concurrently accounting for differences among countries while avoiding the loss of information in DEA analysis using a large number of DMUs.

When interpreting a country's performance during the first year of the pandemic, a crucial consideration arises from the temporal scope of measurements in Model D, spanning a year. Implicit in this timeframe assumption is that COVID-19-related death cases were distributed relatively evenly across the year. However, this assumption does not align with the reality experienced by the majority of countries, which faced multiple waves of the pandemic at varying intervals. For example, Kyrgyzstan and Tajikistan had distinct pandemic experiences despite displaying the highest efficiency in Model D (World Health Organization, 2023). Kyrgyzstan faced challenges during the initial wave, while Tajikistan successfully managed the first wave through stringent restrictive measures. Thus, while Kyrgyzstan's performance was not flawless in the initial wave, a broader evaluation reveals commendable results throughout the entire first year.

The global scale of the COVID-19 pandemic unfolded over an initial two-year period, and each country underwent a unique trajectory in pandemic development. These variations are evident in the timing of epidemic waves and reflected in reported death rates in each country. In light of these considerations, it is advisable to interpret the results of the first year as indicative of the preparation and initial response of a country's healthcare systems rather than a comprehensive assessment of the entire pandemic impact.

A notable strength of our study is the selection of the "death excess" for our primary output. This measure includes both the direct and indirect impacts of the COVID-19 pandemic in a country, offering a comprehensive assessment of the pandemic's influence. This measure distinguishes our study from previous research that did not employed this variable in assessing countries efficiency during COVID-19 pandemic. The incorporation of the "death excess" measure is particularly valuable in addressing a common limitation in research that associated with use of officially reported death numbers, which often fail to report the pandemic's impact.

The COVID-19 pandemic has placed immense stress on health systems. Healthcare had to adapt to the new circumstances while maintaining a commitment to delivering high-quality healthcare. The differences in countries' performance between Model A and Model D can be considered as insights into their resilience during the crisis. However, since these two models employ different output measures, direct comparison of efficiency scores is not feasible. Instead, our focus shifts to comparing the ranks of countries in two models. A decrease in a country's rank between the pre-epidemic Model A and the during-epidemic Model D could signify that the country was well-prepared to provide healthcare under usual circumstances but faced challenges in adapting to the crisis. This nuanced perspective adds depth to our understanding of healthcare system readiness and resilience in the face of the pandemic.

Interesting findings emerged from the Tobit regression, revealing the health workforce (physicians and nurses) as the most influential factor in determining a country's efficiency. This observation is inherently logical given that physicians serve as the primary unit in healthcare systems, forming the cornerstone around which the majority of health services are built. In typical circumstances, as evidenced by Model A, a reduction in the rate of physicians correlates with improved efficiency, reflecting optimization of the system. However, the shift in the direction of Physicians effect occurs during the pandemic (Model D). This effect was particularly pronounced in EU countries. The increase in the nurses' rate emerges as the positive factor impacting the system's efficiency in the EU group.

A contemporary trend involves a reduction in the number of physicians within healthcare systems, adopting approaches such as redistributing workloads to nurses, transitioning health services to homecare, and embracing telemedicine. However, our study underscores the need for caution in embracing this trend. The results suggest that a system adapted to day-to-day needs may struggle to cope effectively with a crisis if the reduction in the number of physicians is too drastic. This insight emphasizes the critical role of physicians and nurses, especially during unprecedented events like a pandemic, where their presence and capacity significantly contribute to healthcare system resilience and efficiency.

Comparisons with prior studies that assessed countries' efficiency before the pandemic reveal certain similarities in trends, despite notable differences in methodological approaches, in inputs measures, and the selection of countries in the analysis (Ahmed et al., 2019; Behr & Theune, 2017; Gavurova et al., 2021; Pérez-Cárceles et al., 2018). Conversely, when examining countries' efficiencies during the COVID-19 pandemic, particularly in studies using COVID-19 death rates as an output measure in DEA (Breitenbach et al., 2021b; Keskin & Delice, 2023; Lupu & Tiganasu, 2022; Mourad et al., 2021; Ordu et al., 2021) also somewhat consistent with our results. The difference became notable when contrasting our study with those that selected countries from various global regions without accounting for variations in healthcare system performance within these regions (Breitenbach et al., 2021b; Keskin & Delice, 2023; Mourad et al., 2021; Ordu et al., 2021). However, studies conducting cross-country comparisons within the same region exhibit similar efficiency ranking trends to our study, even when making distinct choices regarding input variables (Lupu & Tiganasu, 2022). The differences might be due to use of "excess death" in our study as a more comprehensive assessment of COVID-19's impact. These findings emphasize the importance of considering multiple factors and adopting a nuanced approach when assessing countries' healthcare system efficiency, recognizing the dynamic nature of the global healthcare landscape.

Conclusions

Evaluating healthcare systems is crucial for improving performance, facing unforeseen challenges, and refining policies. The COVID-19 pandemic highlights the need to assess healthcare efficiency, comparing responses to sudden challenges and ensuring the continuous delivery of essential services. Cross-country comparisons are essential for understanding the complex factors influencing healthcare system efficiency. This evaluation, both before and during the pandemic, serves as a crucial step in assessing the resilience of healthcare systems, aiding in identifying best practices and developing improved resilience for future crises.

Our analysis of healthcare system efficiency has yielded valuable insights. The methodological approach of results interpretation presented in the article has allowed to discern nuances in performance across diverse countries. While interpreting the results, it is crucial to acknowledge the complexity of healthcare systems, the unique temporal variations in pandemic trends, and the considerations associated with DEA methodology. The Tobit regression highlighted the pivotal role of health workforce and particularly physicians, emphasizing its significance during the pandemic, where an increase in this factor positively influenced system efficiency. Sensitivity analyses, focusing on regional subsets like the CIS and the EU, provided additional layers of understanding in countries efficiency. Our findings caution against the recent trend of reducing the number of physicians within healthcare systems, emphasizing the importance of maintaining resilience in the face of crises. Furthermore, the inclusion of the "death excess" measure as the primary output indicator enhanced the depth of our assessment, capturing both direct and indirect impacts of the pandemic. The study contributes valuable insights into the assessment of healthcare system resilience by identifying frontrunner systems and, consequently, best practices during the COVID-19 pandemic. This information equips health authorities and policymakers with assessment tools for healthcare systems and underscores the need for tailored approaches to improving the system's efficiency.

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APPENDIX

The cross-country efficiency by countries groups (The results of DEA analysis)

Groups	Model A		Model D	
	Rank	Efficiency	Rank	Efficiency
CIS countries				
Azerbaijan	4	0.882052	4	0.996424
Belarus	6	0.408336	6	0.947274
Kazakhstan	5	0.725684	5	0.951914
Kyrgyzstan	1	1	1	1
Moldova	1	1	3	1
Tajikistan	3	0.947208	1	1
EU countries				
Latvia	1	1	4	1
Lithuania	7	0.857175	6	0.986176
Estonia	1	1	5	1
Poland	1	1	3	1
Romania	1	1	1	1
Slovakia	6	0.953268	7	0.951096
Czechia	8	0.775872	8	0.940919
Bulgaria	1	1	1	1