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ORIGINAL RESEARCH

Examining operational efficiency with prudent risks of Covid-19: a contextual DEA analysis with an undesirable intermediate measure

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Abstract

In the wake of the losses of human lives and disruption to the world economy caused by the spread of the COVID-19 pandemic, it has become imperative to assess the effectiveness of containment strategies adopted by countries. The success of any containment strategy of achieving low mortality and high recovery rate depends on the efficient utilization of available but limited resources, such as number of hospital beds and healthcare workers. While the spreading pattern of the pandemic has been researched heavily, there is limited research that comprehensively focuses on the efficient utilization of available resources to achieve the desired aims of low mortality and high recovery. In order to close this research gap, we employ a two-stage network data envelopment analysis (DEA) to identify the inefficiency in the process and resolve the resource constraints by considering medical and non-medical (administrative) interventions as two serial stages. The number of infected people is treated as the intermediate product, which is an undesirable output of the first stage and subsequently enters the second stage as an input. This network DEA model successfully addresses the conflict between the two stages over the handling of infected people and assesses the vulnerabilities of the countries against the transmission rates of the disease in the respective countries. Thus, the objective of this study is to develop a well-coordinated plan for different government agencies to jointly mitigate the risk under constrained resources. The findings reveal that almost 60% of the Organization for Economic Cooperation and Development (OECD) countries have used their resources suboptimally and are producing, on average, almost half the amount of the maximum possible outputs. As a sizeable amount of inefficiency can be explained by varying economic and demographic factors, such as health expenditure and the proportion of the aged population, the efficiency evaluation has been revisited with adjustments for unfavorable externalities. The analysis and its implica-

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tions can help policymakers formulate optimal resource plans and identify potential areas for improvement.

Keywords COVID-19 · Network DEA · Non-radial measure · Healthcare performance

1 Introduction

The Covid-19 pandemic caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) has inflicted irreparable loss to human lives and national economies. The total number of confirmed cases has reached, globally, 572,239,451 (as of 29 July 2022), with 6,390,401 million deaths (WHO, 2022). With restrictions on travel and social interaction, the aggregate demand in the economy in the first half of 2020 was curtailed. Industrial commodities, e.g., metals, oil, rubber, and vehicle parts, as well as the energy sector, were expected to experience an unprecedented collapse (The World Bank, 2020). This abrupt disruption of the global economy caused by the pandemic resulted in the steepest fall in output production, output price, and employment, and a steady rise in inflation (J.P.Morgan, 2020; The World Bank, 2022). Against this backdrop, the judicious use of inputs, e.g., capital and labor, taking into account the macro-economic factors like demographic and socio-cultural elements, have been among the primary objectives on the agenda of global economic planning and policymaking.

While scientists have struggled to find a universal vaccine for the virus, the world leaders and policymakers are constantly on the lookout for feasible strategies to contain and slow down its spread (Gates, 2020), an approach which is supported by research (Hansun et al., 2020). Mitigating the damages requires policy measures beyond just the medical exercise and should encompass operational, logistical, and financial solutions (OECD, 2020a). Also, the overall performance of a country is jointly determined by medical and non-medical countermeasures (OECD, 2020a). The non-medical measures include the imposition of lockdowns, reduction in the number of social gatherings, easy access to information, maintaining social distancing, disinfection, and isolation measures. On the other hand, medical measures are primarily related to the hospitalization of the infected people and treatment thereafter. The future course of Covid-19 is still unknown and in the absence of a universal vaccine, the non-medical measures remain important as a first line of defense against the pandemic (Hansun et al., 2022). They relieve the health sector of the imminent pressure by curbing the peak of the outbreak and spreading it over a longer period of time (Fong et al., 2020). Thus, when this situation is examined as a single-stage process, unlike in a holistic approach, ignoring the internal production flows the target setting and the benchmarking of the standard practices will not be realistic. In response to this, this study opens up the "black-box" and treats medical and non-medical stages as individual systems interlinked by the number of infected people.

As the demand for capital and healthcare personnel is ever-increasing and the resources are limited, it is imperative that the medical and administrative resources are utilized efficiently and effectively. When the healthcare supply chain is stretched thin, the ideal outcome depends on the optimal allocation of resources (e.g., testing kits, equipment, masks, etc.) based on the vulnerabilities of the respective communities (Govindan et al., 2020). Thus, the affected countries need to identify and optimize the key resources of medical and non-medical organizations in view of the vulnerabilities of the nations to credible and imminent threats. There is a lack of research to assess the resource utilization at a broad level to contain the spread of the pandemic. Furthermore, the performance of a country in dealing with the pandemic depends not only on the performance of its administrative offices and healthcare facilities, but also on the interactions and effective coordination between the two. This has led us to examine the relative efficiency of medical and non-medical interventions, as well as their coordination, which adds up to country-level performance.

The expected outcomes of non-medical interventions are to identify the maximum number of infected people and maximise the number of tests performed (Fong et al., 2020). A carefully planned testing scheme leads to better contact tracing and a higher number of people who are isolating, which will eventually slow down the spread. As the number of infected people is an outcome of testing, tracing, and tracking, the primary objective of testing is to identify as many infected people as possible. At the same time, administrative efforts aim to reduce the number of infected people, which can be enhanced multifold by managing smart data and using information and communication technology (ICT) to record and predict a possible transmission. The Organization for Economic Cooperation and Development (OECD) countries are at different levels of maturity and development in terms of healthcare reach and use of ICT infrastructure in controlling the spread of the disease. The socioeconomic parameters and preparedness of governments are broadly captured using affordable healthcare and policies to encourage telemedicine and the smarter use of data for surveillance and tracking.

Although containment and mitigation policies are pivotal tools in curbing the pandemic, the healthcare sector is responsible for more direct and measurable actions in treating the infected people. The infected people as identified in the first stage are admitted for treatment. Thus, they are considered as a major input to stage-2. Doctors and beds are widely regarded as two key resources (Mark et al., 2009). In this study, the number of acute care beds that are used to treat severe cases in critical care is regarded as a measure of the capacity of healthcare to treat critically sick patients. The objective of the medical units is to maximize the number of recovered patients and reduce the number of deceased patients. Hence, the latter is treated as an undesirable output.

Developing countries face challenging trade-offs as different social services compete with healthcare for public funds. The mean per capita health expenditure grew by 17% in the developing countries, whereas OECD countries observed only 7% growth between 1997 and 2004 (Mirmirani et al., 2011). These numbers indicate OECD countries provide adequately stable health services. Furthermore, the impact of Covid-19 at local and regional levels, particularly for the functioning of subnational (e.g., municipalities) bodies, varies by country. Such heterogeneity across territorial boundaries has strong implications for crisis management (OECD, 2020c). Therefore, the relative evaluation of countries from different continents with large variations in governance structure and policymaking is understandably partial. To reduce this systematic inequity, in this study, the OECD countries are regarded as independent Decision-Making Units (DMUs) in the evaluation process. The dependency between non medical measures and medical responses has been integrated into the model as the two stages of a DMU connected in series (Fig. 1).

In this paper, we investigate the efficiency and effectiveness of different OECD countries by analyzing the performance of their administration and healthcare sectors, and the coordination between them to mitigate the loss of health and human lives. We employ a two-stage network data envelopment analysis (DEA) framework to assess the performance of countries, considered as DMUs. DEA is a well-known data-enabled performance evaluation technique (Zhu, 2022; Zhu & Charles, 2021) that has proven effective in a range of fields, facilitating decision-making around the world (Charles et al., 2021). The administrative office and healthcare sector have been regarded as the two stages of the network DEA. A slack-based DEA model is applied to a two-stage process to determine the overall inefficiencies and then decompose these into stage-level inefficiencies. A conflict arises between consecutive stages due to the dual utility of the number of infected people as an intermediate measure (Chen et al., 2010a). The number of infected people is treated as undesirable factor, as both health care and administrative authorities would want to minimize it.

As will be shown, the results indicate that countries like Germany, Ireland, etc., and their independent authorities, such as administrative offices and medical units, referred to as stages of the overall DMUs in this study, have performed most efficiently in managing the spread of the pandemic. On the other hand, countries like the United Kingdom, the Netherlands, etc., and the administrative offices of Slovenia, Finland, and medical units of the United Kingdom and the Netherlands have performed poorly and can improve their efficiency level substantially. The contribution that this study makes to the area of Operations Research applications in disaster or epidemic management is threefold. First, it emphasizes the coordination required among various government agencies by including the intermediate product between the two stages. Second, it accounts for the uncontrollable environmental variables that influence the effectiveness of the containment strategies. Third, it prescribes particular areas of concern for inefficient countries in accordance with their vulnerabilities and imminent threats.

The remainder of the paper is organized as follows. In Sect. 2, we review the previous relevant literature. Section 3 introduces the proposed model and its novelty. Section 4 demonstrates the context-based application to OECD countries and analyzes the results. Section 5 provides empirical analysis in the presence of negative externalities, risk factors and various co-ordination efforts. Section 6 outlines the managerial implications for the stakeholders and Sect. 7 concludes.

2 Prior research

All across the world, domain experts like biologists, virologists, epidemiologists, and statisticians have been equally baffled by the questions of how to stabilize the pandemic scenario and eventually stop it from spreading. The range of solutions is varied, starting from administrative control to applying concepts from the engineering domain, such as control theory (Stewart et al., 2020). A considerable amount of research has been conducted on a track, trace, and treat approach in the early stages of any emerging pandemic. Since SARS and the 2009 influenza pandemic showed us that non-medical measures can only flatten the peak of the pandemic curve, and so was the experience with Covid-19, policymakers need to understand the urgency of implementing an effective strategy in a timely manner (Watkins, 2020). Preventing local transmission, mobilizing human, physical, and financial resources (Tangcharoensathien et al., 2021) and governance alacrity in disaster management and communication of risk awareness among the citizens (Renda & Castro, 2020), are some of the non-medical measures and areas of concern proven to be effective in controlling an epidemic.

Since the development of vaccines against several diseases, e.g., dengue, is still underway, vector control is the best tool available to battle these diseases (Rodrigues et al., 2012). These models lead to possible disease-free equilibriums. Since the micro-organisms responsible for such diseases often change their biological characteristics over time, the dynamic behavior of those diseases has drawn a lot of attention among scientific communities. For instance, the dynamics of the H1N1 virus spread are captured using a range of models. Further, data fitting uses a variety of mathematical tools to measure the fit of experimental data in different solutions that are used (Skovranek et al., 2012). Such models have recently been extended using fractional-order models, where the state of the system depends not only on the previous state but on all the historical states that led to the previous state. Ding et al. (2011) used fractional-order models to optimize optimal control problem for a HIV-immune system. Agent-based Social Simulation facilitates the analysis of the future state of the pandemic allowing for adjustments for specific characteristics of the disease, population behavior, and social interventions (Lorig et al., 2021).

Mathematical models can provide useful insights into the spread pattern and dynamics of the epidemic. The most widely used among such models are compartmental models, where the population is compartmentalized into different categories: Susceptible(S), Infectious(I), Exposed(E), and Recovered(R) (Murray, 2001). Depending on the pattern of flows among the compartments, models can be of different types: SIS, SI, SIR, SEIR, etc. (Murray, 2002). These models can project various parameters of the epidemic, such as the transmission rate, total number of infected people, duration of the epidemic, and the reproductive rate (González-Parra et al., 2014). The outcome of different policies can also be determined. In the recent epidemics of H1N1 and Ebola, this technique has been extensively used. Apart from that, time series analysis was explored to predict the number of infected people and deaths (Upadhyay & Roy, 2016). The flow of disease from one compartment to another depends on the characteristics of the disease and is a function of preventive measures. The order in which they appear in popular models like SEIR, SIR, SEI, SI, SIS, etc., shows the development of the disease (Hethcote, 2000). A time-dependent SEIR model was developed (Whang et al., 2011) as a model for the transmission dynamics of TB and to propose optimal treatment strategies for TB in South Korea using optimal control (OC) theory. However, some researchers have studied the containment strategies as policy drivers, e.g., Christensen and Painter (2004) discussed how much of the decisions taken by governments and administrations in the face of the pandemic are rational or motivated by some agendas—as seen from the garbage can perspective.

The majority of the management research in healthcare efficiency has focused on micro-elements like hospitals, health centers, and so on. For example, Kirigia et al. (2013), Mishra et al. (2020), Kontodimopoulos and Niakas (2005), Arfa et al. (2017) analyzed health centers, hemodialysis centers, safety in hazardous waste-recycling facilities, and district hospitals; and Özgen and Şahin (2010) examined pharmaceutical sectors and dialysis sectors. However, there is a lack of focus on assessing healthcare efficiency in a broader scale, e.g., at state or national level. Unless the health sector efficiency is studied at the macro-level, countries will find it difficult to provide better healthcare services with the available resources.

The coordinated approach by several departments under the government and private sector towards controlling the outbreak calls for a network DEA (NDEA) approach, rather than a traditional black-box approach (Tone & Tsutsui, 2008; Pandey & Singh, 2021). In complex production structures, NDEA has been successfully applied to draw more detailed inferences on areas such as banking (Avkiran, 2015), sports (Kao, 2016), and airlines (Duygun et al., 2016) and sometimes under uncertainty (Pandey & Singh, 2022; Lio & Liu, 2018). Collaboration and trust in humanitarian settings result in agility and efficiency in disaster management tasks (Dubey et al., 2022). When multiple agencies are involved in the relief operations, information sharing is verified as an important enabler of swift-trust, as per commitment-trust theory (Dubey et al., 2019). Several research studies have reported the major challenges and effective strategies to counter the outbreaks for various infectious diseases, for example, Ebola (Jacobsen et al., 2016), Influenza (Whitley et al., 2006), and Covid-19 (Baveja et al., 2020). However, out of 182 countries, as many as 32 (18%) countries have low readiness and 46 (25%) countries have non-existent infrastructural support, as per 18 national-level performance indicators (Jacobsen, 2020).

Anell and Willis (2000) introduced resource profiling as a better way for international comparisons of healthcare systems. The healthcare spending patterns of the US and OECD countries have been studied by Anderson et al. (2004). Cost efficiency of healthcare services in developed (OECD countries) or in-transition economies plays a significant role in the provisioning of quality care at affordable prices (Mirmirani et al., 2011).

In light of the importance of COVID-19 pandemic containment and these two streams of literature, we identify relevant factors and refine the use of NDEA for context-based performance evaluation of OECD countries through their respective administrative and health care sectors.

3 Theoretical backgound

3.1 Disposability assumption

In traditional DEA, the technology is defined in terms of the Production Possibility Set (PPS) where the characteristic function of technology for constant returns-to-scale is given by $T = \{(x, y)|\lambda X \leq x, \lambda Y \geq y, \lambda \geq 0\}$, where input vector x produces output vector y. The intensity vector λ represents the comparative weights of the observed set of inputs (X) and outputs (Y).

Various forms of relationships between bad output and input or output are assumed in the literature: e.g., substitutable relation between good input and bad input (Reinhard et al., 2000); or, expressing the bad output as a by-product of good output (Adler & Volta, 2016; Färe et al., 2005). Nevertheless, these forms fail to meet various conditions of production economy (Coelli et al., 2007). Here, we make a more reasonable assumption that the bad outputs (b) display weak disposability properties:

I. If $(x, y, b) \in T$, then $(x, y', b) \in T$ for any $y' \leq y$,
II. If $(x, y, b) \in T$, then $(x, \theta y, \theta b) \in T$ for any $0 \leq \theta \leq 1$,
III. It says if $(x, y, b) \in T$ and $b = 0$, then $y = 0$.

The first condition states the strong disposability of good outputs. However, a smaller output amount with fixed input values would deteriorate the efficiency score. For example, if with the same amount of lockdown days and financial package, the number of tests done in a country is reduced, then its efficiency will also be reduced as a result. The second condition ensures the weak disposability of bad outputs. It asserts that to reduce bad output, some amount of good outputs has to be foregone. In the current context, when a higher amount of resources is engaged in carrying out testing, a smaller amount of resources would be available to enforce social measures, which would result in a higher number of infected people and vice versa. Note that the second condition holds for the points on the efficiency frontier, i.e., efficient DMUs. In other words, bad outputs are considered the by-products of good outputs. However, in the case in point, the total number of recovered patients and deaths do not share the same supplement relationship. If the number of patients recovered was high, then the number of deaths would be reduced. These three axioms will jointly determine the direction vectors of the respective outputs (both good and bad), whether they will be increased or decreased, and whether these changes are interdependent or not.

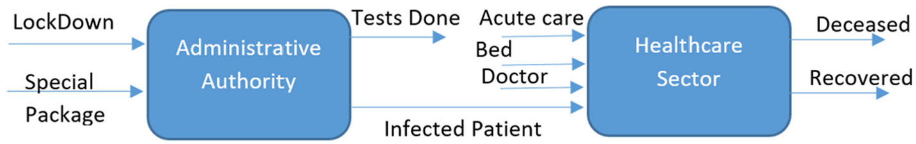


Fig. 1 A two-stage processing model against Covid-19

3.2 Conceptual framework

Overall, the number of days of lockdown (in days) and the special financial aid (in billion USD) are used as exclusive inputs for the first stage. Similarly, the number of acute care beds, doctors, and general beds represent exclusive inputs for the second stage. The exclusive output of the first stage is number of tests carried out. The infected people identified in the first stage are admitted to the second stage for medical treatment. The recovered and deceased patients from the second stage are exclusive good and bad outputs, respectively. Figure 1 demonstrates the network structure of the stages of the generic DMUs.

The efficiency evaluation using DEA can be carried out in the context of two different approaches: radial and non-radial methods. Furthermore, each of the two approaches could either be input or output-oriented. The radial measure of efficiency (Charnes et al., 1981) finds out the maximum proportional augmentation of all outputs or maximum proportional reduction in all inputs. However, radial models have been criticized for having low discriminatory power (Podinovski & Thanassoulis, 2007). The non-radial measure of efficiency evaluation has been proposed (Thanassoulis & Dyson, 1992) to maximize the reduction (augmentation) of the proportion of each input (output) surplus (slack) with regard to input (output) simultaneously.

Apart from non-radial inefficiency, this study accounts for the interdependency between administrative and healthcare stages for a more holistic view of the two-stage network system. In the output-oriented form, along with the three exclusive outputs—namely, tests done, the number of deceased, and the number of recovered patients—the number of infected people is also optimized simultaneously. For a usual intermediate product that is a desirable output of stage-1, it is in the interest of stage-1 to increase its value. However, such a decision by stage-1 would negatively affect the efficiency of stage-2 as its input consumption would increase. In the proposed model, stage-1 tries to minimize the number of infected people (intermediate product) as it is an undesirable output, and this converges with the effort by stage-2, which is also trying to minimize its input consumption. Considering the objective of the OECD countries, the variable returns-to-scale (VRS) output-oriented non-radial DEA model is formulated in (1).

For DMU j, let x_{ij} and y_{rj} denote the ith input and rth output, respectively. Similarly, let b_{th} and z_{dj} denote the tth bad output and dth intermediate measure, respectively. The set of explicit input, output, and undesirable output of stage k is denoted by I_k, R_k, and T_k, where the stage is indexed by k and D denotes the set of intermediate measures. The proposed output-oriented model is formulated as follows:

$$
\begin{aligned}
&\text{Max } \pi_o \quad \textstyle\sum_{r\in R_1\cup R_2} \frac{S_r^-}{y_{ro}} + \sum_{d\in D} \frac{S^d}{z_{do}} + \sum_{t\in t_1\cup t_2} \frac{S_t^+}{b_{to}}\\
&\text{subject to}\\
&\sum_{j=1}^{n} \lambda_j^1 x_{ij} \le x_{io}, \forall i \in I_1,\\
&\sum_{j=1}^{n} \lambda_j^2 x_{ij} \le x_{io}, \forall i \in I_2,\\
&\sum_{j=1}^{n} \lambda_j^1 y_{rj} = y_{ro} + S_r^-, \forall r \in R_1,\\
&\sum_{j=1}^{n} \lambda_j^2 y_{rj} = y_{ro} + S_r^-, \forall r \in R_2,\\
&\sum_{j=1}^{n} \lambda_j^1 z_{dj} = z_{do} + S_d, \forall d \in D,\\
&\sum_{j=1}^{n} \lambda_j^2 z_{do} \le z_{do}, \forall d \in D,\\
&\sum_{j=1}^{n} \lambda_j^1 b_{tj} = b_{to} - S_t^+, \forall t \in T_1,\\
&\sum_{j=1}^{n} \lambda_j^2 b_{tj} = b_{to} - S_t^+, \forall t \in T_2,\\
&\sum_{j=1}^{n} \lambda_j^1 = 1,\\
&\sum_{j=1}^{n} \lambda_j^2 = 1,\\
&\lambda_j^1, \lambda_j^2 \ge 0, \forall j = 1 \ldots n.
\end{aligned} \tag{1}
$$

The slacks of the good outputs and the surplus of the undesirable outputs as fractions of the respective observed outputs are simultaneously maximized in (1). There are two PPSs for the network system, one for each of the stages, as opposed to only one PPS in the 'black box' approach. The two sets of weight (intensity) vectors, λ_j^1 and λ_j^2, specify the two efficiency frontiers for the two stages.

It may be noted that model (1) reports the fraction of the total amount of inefficient outputs. One may conclude that the higher the slack, the smaller the efficiency score. From a productivity perspective, the efficiency score is given as $\theta_o = \frac{1}{1+\pi_o}$. Clearly, when there is no shortfall of intended outputs, i.e., $\pi_o = 0$, the efficiency is full, i.e., $\theta_o = 1$. In other words, only strongly efficient DMUs (DMUs with all output slacks as zero) are ranked as efficient units. It is important to mention that θ_o cannot be interpreted as the radial increment of outputs. The efficiency score θ_o expresses relatively how many times bigger the aggregated wastages in the output of observed DMU are with respect to the reference DMUs against which it is evaluated.

Total slacks (surplus) in good (bad) output of the overall system can be decomposed and associated with the constituent stages. Thus, inefficiencies in stage-1 and stage-2 are derived from: $\pi_o^1 = \sum_{r\in R_1} \frac{S_r^-}{y_{ro}} + \sum_{d\in D} \frac{S^d}{z_{do}} + \sum_{t\in t_1} \frac{S_t^+}{b_{to}}$ and $\pi_o^2 = \sum_{r\in R_2} \frac{S_r^-}{y_{ro}} + \sum_{t\in t_2} \frac{S_t^+}{b_{to}}$. For the generic system, we have $\pi_o = \pi_o^1 + \pi_o^2$. The respective efficiencies are given by:

$$\theta_o^1 = \frac{1}{1+\pi_o^1},\ and\ \theta_o^2 = \frac{1}{1+\pi_o^2}.$$

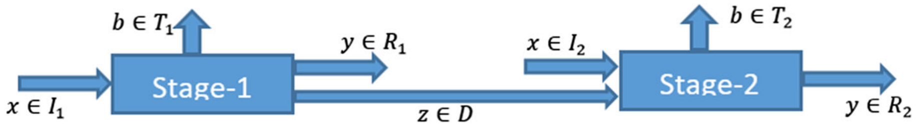


Fig. 2 Conceptual two-stage process

Note that the surplus (s_d) in intermediate output (z_{do}) appears in the objective function as an output of stage-1. From the constraints corresponding to the intermediate measure in model (1), we get:

$$\sum_{j=1}^{n} \lambda_j^2 z_{dj} \leq z_{do} = \sum_{j=1}^{n} \lambda_j^1 z_{dj} - s_d \text{ Or, } \sum_{j=1}^{n} \lambda_j^2 z_{dj} \leq \sum_{j=1}^{n} \lambda_j^1 z_{dj} \tag{2}$$

The above equation infers that the target input consumption of stage-2, $\sum_{j=1}^{n} \lambda_j^2 z_{dj}$, cannot exceed the amount of the intermediate measure produced by stage-1, i.e., $\sum_{j=1}^{n} \lambda_j^2 z_{dj}$. However, an unused intermediate measure is produced if $\sum_{j=1}^{n} \lambda_j^2 z_{dj} < \sum_{j=1}^{n} \lambda_j^1 z_{dj}$. The amount within the system that is not accounted for is $\sum_{j=1}^{n} \lambda_j^1 z_{dj} - \sum_{j=1}^{n} \lambda_j^2 z_{dj}$.

Intermediate products are determined in two ways: "free" link and "fixed" link approach. In the free link approach, the optimal intermediate product can take any value, i.e., it can increase, decrease, or remain unchanged. In the "fixed" link approach, on the other hand, the target intermediate products are fixed at their present values. In reality, model (1) should be considered unrealistic or wasteful. To ensure that all the intermediate measures generated are consumed within the system without leaving any excess or shortfall and its value can be altered while attempting to optimize the overall efficiency, a "free" link approach is followed, i.e., $\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}$.

3.3 Proposed model

3.3.1 Undesirable intermediate measure

To make the model reflect the reality of the situation, as depicted in Fig. 1, the intermediate measure needs to be incorporated into the DEA framework as an undesirable output of stage-1.

In conventional NDEA (Fig. 2), a point of conflict arises between the two stages when stage-1 tries to increase the intermediate measures as its outputs, which leads to worsening of stage-2 efficiency with higher inputs (Chen et al., 2010a). However, in the current context, the undesirability of intermediate measures obviates the conflict by making the reduction in the intermediate measures a common goal of both the stages. In Fig. 1, the only intermediate measure produced in stage-1 is also the only bad output from stage-1. The corresponding DEA model is formulated as follows:

$$\begin{aligned}
&\text{Max } \pi_o \quad \textstyle\sum_{r\in R_1\cup R_2} \frac{S_r^-}{y_{ro}} + \sum_{d\in D} \frac{S^d}{z_{do}} + \sum_{t\in t_1\cup t_2} \frac{S_t^+}{b_{to}} \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j^1 x_{ij} \le x_{io}, \forall i \in I_1, \\
&\sum_{j=1}^{n} \lambda_j^2 x_{ij} \le x_{io}, \forall i \in I_2, \\
&\sum_{j=1}^{n} \lambda_j^1 y_{rj} = y_{ro} + S_r^-, \forall r \in R_1, \\
&\sum_{j=1}^{n} \lambda_j^2 y_{rj} = y_{ro} + S_r^-, \forall r \in R_2, \\
&\sum_{j=1}^{n} \lambda_j^1 z_{dj} = z_{do} - S_d, \forall d \in D, \\
&\sum_{j=1}^{n} \lambda_j^2 z_{do} = z_{do} - S_d, \forall d \in D, \\
&\sum_{j=1}^{n} \lambda_j^1 b_{tj} = b_{to} - S_t^+, \forall t \in T_1, \\
&\sum_{j=1}^{n} \lambda_j^2 b_{tj} = b_{to} - S_t^+, \forall t \in T_2, \\
&\sum_{j=1}^{n} \lambda_j^1 = 1, \\
&\sum_{j=1}^{n} \lambda_j^2 = 1, \\
&\lambda_j^1, \lambda_j^2 \ge 0, \forall j = 1 \ldots n.
\end{aligned} \tag{3}$$

Model (3) is different from Model (1) in the way it treats the intermediate measure, where it implies: $\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}$, i.e., it is equal for both the stages. This equality constraint ensures that the entire amount of intermediate measure produced is completely consumed within the system.

In this study, models (1) and (3) denote two different ways to treat the intermediate products. Model (1) treats intermediate products as a desirable output, which is not valid in the context of the Covid-19 pandemic, where the number of infected patients functions as an intermediate product. Thus, a new DEA framework, model (3), was developed to correctly reflect the ground reality, which is that infected patients act as an undesirable output from stage-1. Therefore, in keeping with the treatment of undesirable outputs, the target values of intermediate products are minimized. In other words, model (3) follows the "free" link approach with the added constraint that the target value cannot exceed the current value.

The usual outputs are maximized in DEA, as shown in the following constraint for stage-1:

$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} \ge z_{do}, \forall d \in D,$$

Or, in the slack-based approach, it can be re-framed as (refer to the stage-1 constraints in (1)):

$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} = z_{do} + S_d, \forall d \in D.$$

The intermediate products act as inputs for stage-2, and are determined by the following constraint:

$$\sum_{j=1}^{n} \lambda_j^2 z_{dj} = z_{do} - S_d, \forall d \in D.$$

In model (1), a larger value of $z_{d,j}$ would lead to a more efficient stage-1. But, it also implies an inefficient stage-2. This conflicting dual role of intermediate products is studied at great length in the previous literature (Chen et al., 2009).

As already discussed, in the proposed model the intermediate product is treated as an undesirable output. Therefore, the stage-1 constraint representing the intermediate product now takes a different form, as follows:

$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} \leq z_{do}, \forall d \in D.$$

Since there is no change in the role of the intermediate product as an input to stage-2, the corresponding constraint remains unchanged:

$$\sum_{j=1}^{n} \lambda_j^2 z_{dj} \leq z_{do}, \forall d \in D.$$

It is clear that both the stages share a common goal of minimizing the intermediate products. Therefore, the conflict is resolved between the two stages on how the intermediate measures should be optimized.

Lemma 3.1 *A generic system is efficient if and only if both the stages are efficient.*

An efficient generic system has an objective function as zero at the optimality. Thus, if $\pi_o = 0$, it can be concluded that $\pi_o^1 = \pi_o^2 = 0$. Hence, both stages are efficient.

An inefficient generic system has a non-zero slack, i.e., $\pi_o > 1$. Hence, at least one stage has a non-zero slack, $\pi_o^p > 0$, while the other stage can be efficient $\pi_o^{p'} = 0, \forall p' \neq p$. A generic DMU is strongly efficient if the component stages are all strongly efficient (Castelli et al., 2010).

Lemma 3.2 *Every stage has at least one efficient DMU in (3). However, there might arise a situation where no overall DMU is fully efficient.*

The two stages in the proposed model have their own production possibility set (PPS) (Moreno & Lozano, 2014). Thus, there are two separate PPSs with two different efficiency frontiers. The PPS of stage-1 is formed by the following set of inequalities:

$$\sum_{j=1}^{n} \lambda_j^1 x_{ij} \leq x_{io}, \forall i \in I_1,$$

$$\sum_{j=1}^{n} \lambda_j^1 y_{rj} = y_{ro} + S_r^-, \forall r \in R_1,$$

$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} = z_{do} - S_d, \forall d \in D,$$

$$\sum_{j=1}^{n} \lambda_j^1 b_{tj} = b_{to} - S_t^+, \forall t \in T_1.$$

By the virtue of variable returns-to-scale (VRS), the DMUs with the smallest and largest output production are always part of the efficiency frontier. Therefore, there will always be at least one efficient DMU for stage-1. Using the same logic, it can be concluded that stage-2 will also have at least one efficient DMU.

The overall efficiency is calculated based on the aggregated slack and surplus values in each of the stages. Further, efficiency in one stage does not guarantee efficiency in the other stage. Because of that, when no DMU in the entire dataset operates with zero slack and surplus values in both stages, each DMU incurs a certain amount of inefficiency, however small, in the overall approach. As a result, there is no DMU that is overall efficient. Though such kinds of instances are not very common (Moreno & Lozano, 2014), they can be found in the DEA literature (Gong et al., 2018; Singh & Ranjan, 2018). Each of the stages has its own PPS. Therefore, there is no guarantee that if stage-1 of a particular DMU is efficient, then stage-2 of the same DMU will also be efficient. Thus, when there is no common efficient DMU between the two stages, none of the generic systems become efficient. Although rare, such results can be found in the DEA literature (Gong et al., 2018; Singh & Ranjan, 2018).

The dual of model (3) is formulated as the following multiplier DEA model:

Theorem 3.3 *The proposed DEA model has more discriminatory power than a slack-based 'black-box' approach and also than a radial efficiency approach in network DEA.*

In a single-stage DEA framework, the situation could have been modeled as:

$$\begin{aligned}
&\text{Max } \pi_o = \sum_{r=1}^{R} \frac{S_r^-}{y_{ro}} + \sum_{t=1}^{T} \frac{S_t^+}{b_{to}} \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io}, \forall i, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro} + S_r^-, \forall r, \\
&\sum_{j=1}^{n} \lambda_j b_{tj} = b_{to} - S_t^+, \forall t, \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0, \forall j = 1 \ldots n.
\end{aligned} \tag{4}$$

It is clear from the principles of Linear Programming that a larger number of constraints reduces the feasibility region, which leads to a worsening of the objective function value. Thus, the black-box model appears to be more lenient in nature when compared to the proposed model. For the radial efficiency approach in network DEA, refer to previous studies by Chen et al. (2009), Kao and Hwang (2014), or Lozano and Gutiérrez (2014). Firstly, we will show that a DMU marked as efficient in those research methods (models (5), (3), or (1) in these three papers, respectively) can be rendered inefficient in our proposed model. Secondly, we will also show that an efficient DMU in the proposed model will always be efficient in those previously developed models.

The efficiency score is determined (as prescribed in the three previous papers) directly from the following constraint (in an output-oriented approach):

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \alpha y_{ro}.$$

For an efficient DMU, the output augmentation rate is one, i.e., $\alpha = 1$. It is possible to have some slacks in some (but not all) of the output variables. Let us suppose that only r_1 has a slack of S_{r1}^{-} in the optimal solution. Note that this results in inefficiency in the proposed model. The conclusion is more obvious if slacks are found in more output variables.

Now, assume that a DMU 0 is efficient in the proposed model. In other words, there is no slack variable, i.e., $S_r^{-} = 0, \forall r$. Clearly, the output constraints hold at equality i.e., $\sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro}$. This shows that DMU 0 is efficient as $\alpha = 1$. As far as the application of OR techniques is concerned, to the best of our knowledge, this study is the first to deploy DEA to measure the efficiencies of the countries in battling the Covid-19 pandemic. The dual model of the proposed framework would help us determine the shadow prices of the input resources and compare the utility of these resources in achieving a better outcome. The linearized dual model is expressed as follows:

$$\begin{aligned}
&\text{Min} \quad \textstyle\sum_{i\in I_1} v_i^1 x_{io} + \sum_{i\in I_2} v_i^2 x_{io} + \sum_{r\in R_1} u_r^1 y_{ro} + \sum_{r\in R_2} u_r^2 y_{ro} + \sum_{d\in D} \omega_d^1 z_{do} + \\
&\textstyle\sum_{d\in D} \omega_d^2 z_{do} + \sum_{t\in T} \alpha_t b_{to} - \mu_o^1 - \mu_o^2 \\
&\text{subject to} \\
&\textstyle\sum_{i\in I_1} v_i^1 x_{io} + \sum_{r\in R_1} u_r^1 y_{ro} + \sum_{d\in D} \omega_d^1 z_{do} - \mu_o^1 \geq 0, \forall j = 1 \ldots n, \\
&\textstyle\sum_{i\in I_2} v_i^2 x_{io} + \sum_{r\in R_2} u_r^2 y_{ro} + \sum_{d\in D} \omega_d^2 z_{do} + \sum_{t\in T} \alpha_t b_{to} - \mu_o^2 \geq 0, \forall j = 1 \ldots n, \\
&v_i^1, v_i^2 \geq 0, u_r^1, u_r^2, \omega_d^1, \omega_d^2, \alpha_t, \mu_o^1, \mu_o^2\ unrestricted, \\
&u_r^1 \leq -(\tfrac{1}{y_{ro}}), \forall r \in R_1, \\
&u_r^2 \leq -(\tfrac{1}{y_{ro}}), \forall r \in R_2, \\
&\omega_d^1 + \omega_d^2 \geq \tfrac{1}{z_{do}}, \forall d1, D, \\
&\alpha_t \geq \tfrac{1}{b_{to}}, \forall t1, T.
\end{aligned} \tag{5}$$

The rth exclusive good outputs of stage-1 and stage-2 are weighed by u_r^1 and u_r^2. The ith exclusive inputs of stage-1 and stage-2 are weighed by v_i^1 and v_i^2. The dth intermediate measure is weighted as ω_d^1 and ω_d^2 for stage-1 and stage-2. The bad output from stage-2 is weighted as α_t. The decision variables of model (4) denote the shadow price of the corresponding constraints of model (3). The variables μ_o^1 and μ_o^2 demonstrate the VRS assumption of the stages. The two stages of a DMU may exhibit different returns-to-scale characteristics. Model (4) minimizes the net cumulative cost of the inputs adjusted for outputs and intermediate measures.

3.3.2 Categorical DEA analysis

There is sufficient research and evidence that shows that countries are facing different levels of difficulties that are beyond the control of their governments (OECD, 2020b). In one of their reports, WHO (WHO, 2020) recognized how the low capacity humanitarian settings are differently impacted by the pandemic. The report discusses a plethora of key public health issues and social conditions in relation to the spread of Covid-19. This violates the primary assumption of a classical DEA model that all the DMUs are homogeneous and comparable.

Therefore, to make the evaluation process unbiased, the countries are classified into groups based on the level of difficulties. The PPS of the DMU in question is constructed only by including DMUs in the same category and in the categories that are in less favorable categories. In the proposed DEA model (3), the weights of the DMUs, not belonging to the PPS of the current DMUs, are assigned zero values:

$$\lambda_j^1, \lambda_j^2 = 0, \; j \nsubseteq PPS.$$

When these constraints are appended to model (3), the solution space would reduce. Consequently, the efficiency score would improve. The new score is termed as "Categorical" efficiency; whereas the efficiency of the previous models, unrestricted by the categorical groups, is termed as "non-categorical" efficiency.

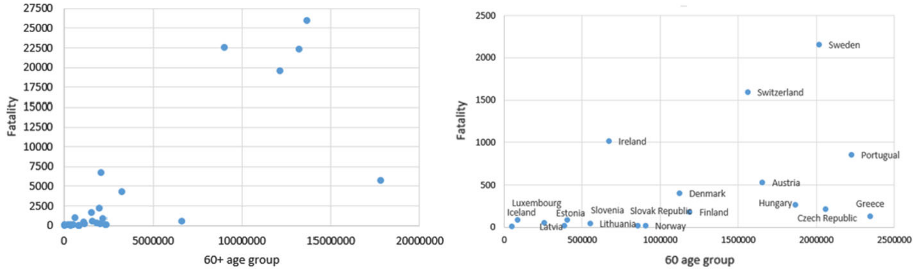
4 Application to OECD countries

The applicability of the propositions made in this paper is demonstrated using the relevant data representing the Covid-19 situation in the OECD countries. The data are collected from different public sources, the OECD library, and WHO situation reports.

There are several difficulties in the collection of data on lab tests, prescriptions, or special visits, particularly for Covid-19 patients. Thus, conventional inputs and outputs parameters for stage-2, i.e., the Health System, follow from the relevant literature (Ersoy et al., 1997; Kirigia et al., 2013). As the number of patients in need of critical care (e.g., ventilation) rises, rationing becomes the only alternative that physicians have (Giacomo Grasselli et al., 2020). Thus, the availability of acute (critical) beds acts as a proxy variable for the preparedness of the health sector to treat any critically sick patients (White & Lo, 2020). As the majority of the Covid-19 patients do not undergo severe conditions, they can also be treated in general beds under observation. The number of beds and doctors signifies the capacity of the medical units in handling a large number of non-critical patients (Khan et al., 2020). Capturing the efficient management of governmental and regulatory authority in strategizing and implementing effective countermeasures is far more challenging due to several limitations in the form of measurability, data availability, and reliability of available information.

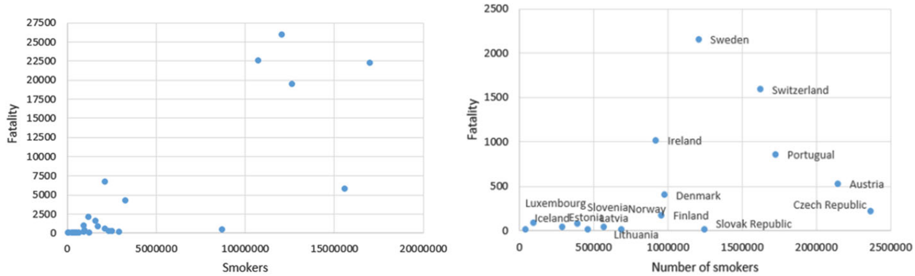
4.1 External factors

This paper aims to identify the cumulative impact of three external factors that would inhibit the recovery and control efforts: population with 60+ age (Lim et al., 2020), per capita health expenditure (Khan et al., 2020), and the number of smokers (Vardavas & Nikitara, 2020). This results in a variation in the transmission rate and mortality rate across the countries. Due to the small sample size of 26 OECD countries, according to rules of ordinary least squares methods Knofczynski and Mundfrom (2008), we use a single variable linear regression to examine the pattern in the fatality rate. The fatality rate appears to have been positively influenced by the number of citizens in the 60+ age bracket, at 1% significance level. In countries with an aged population of less than 2.5 million, the strength of this correlation diminishes from $R^2 = 0.62$ to $R^2 = 0.22$ *significantly* at $p = 0.05$. This means that when



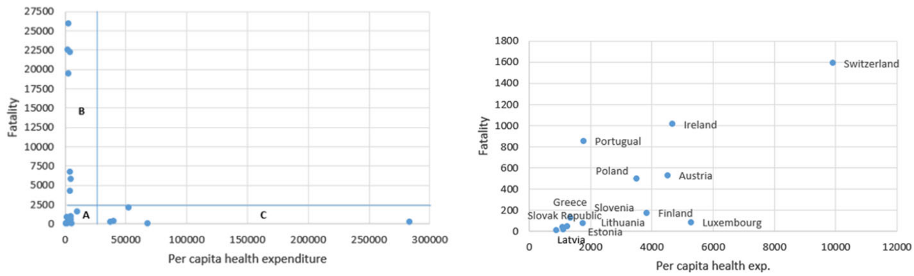
(a) All OECD countries (b) Small population size of 60+ age

Fig. 3 Variation in Fatality rate with population size of 60+ age grp. For **a** all OECD, and **b** small OECD countries



(a) All OECD countries (b) Small OECD countries

Fig. 4 Variation in Fatality rate with number of smokers in **a** all OECD, **b** small OECD countries



(a) Fatality Vs. Per capita health exp. (all countries). (b) Fatality Vs. Per capita health exp. (small countries).

Fig. 5 Effect of health expenditure on fatality

the population is small, the death rate is subject to other factors, such as access to medical treatment, the quality of healthcare service, and so on (see Fig. 3a, b).

The number of smokers in the population is found to be a good explanatory variable ($R^2 = 0.66$) with significant confidence $p < 0.0000$, with a positive relationship between the two variables (coefficient = 0.0012), Fig. 4a. In countries with low fatality, Fig. 4b, the number of smokers in not a good predictor ($R^2 = 0.2$) at 10% significance level.

There is a negative relationship between per capita health expenditure and fatality rate. According to the trend, the graph has been segmented into three categories: A, B, and C in Fig. 5a.

Category A represents the countries that spend very less, e.g., Poland, Portugal, Ireland, and Austria. Fatality rate has a *positive* relationship with per capita health expenditure and the linear association is surprisingly *strong* ($R^2 = 0.6$) and *significant* ($p = 0.001$). The results show that when the per capita health expenditure is low, higher economic support to the health sector makes other socio-economic sectors under-funded Fig. 5b.

Category B denotes the segment of the countries which have a low per capita health expenditure and, consequently, a high rate of fatality with $R^2 = 0.72$ at level $p = 0.016$. In such cases, the fatality rate can be improved by augmenting the healthcare budget, as the coefficient is *highly* negative (-8.52). In other words, economic intervention is badly required for countries like Italy, Spain, France, and the UK, among others. The countries in category C do not show a *significantly* strong relationship between the two variables. Thus, no generic policy changes can be advised based on the observed data.

5 Empirical analysis

In this section, we describe and explain the results obtained by applying the proposed model (3) to the data on Covid-19 in OECD countries. Table 1 reports the descriptive statistics of the input–output variables used in the analysis. At the time of collecting the data, OECD countries are on average 37 days into lockdown with low variation (9 days). However, the number of tests performed, and the infected people have intriguingly high levels of variations, which are almost 150% of the respective means. In the medical sector, general beds with mean 93232.2, have the highest variation (e.g., 145206) among the inputs. The means of the recovered and deceased patients are 14,986 and 4427, respectively. The maximum, minimum, and the difference between the two values of the parameters are shown in “Max”, “Min”, and “Range” rows.

Figures 6 and 7 provide the overall non-radial technical efficiency scores and their distribution, respectively, of the OECD countries. From Fig. 7, we note that the number of efficient DMUs is nine (35%). The average efficiency score is 52.7% (with standard deviation 37.9%), which indicates that the amount of inefficiencies in the evaluated parameters, on an average, is that the total output wastages are cumulatively almost half of the present outputs. The corresponding value for the median is 40%, which indicates that low performing countries are constituting the majority of the countries (Fig. 7). The sheer disparities in efficiency scores are evident from the fact that the bottom 25% of the countries experience less than 20% efficiency, whereas the top 25% of the countries achieve full efficiency. The skewness in the distribution can be observed prominently in the low first and the second quartile values of efficiency scores (19.4% and 40.4%), whereas both the third and fourth quartiles are 100%. In addition, we split the overall efficiency into stage levels, which are shown in Fig. 8a, b.

The primary sources of inefficiencies are listed in Table 2. The OECD countries have a deficit of 157,569 tests performed, given the special financial aid declared by the respective governments. But, the percentage of slack as compared to the total tests that have been successfully conducted is merely 1.87%. Only three countries, Finland, Slovenia, and Estonia are responsible for this deficit Fig. 9a. This analysis reveals that Iceland can be used as a benchmark for improving the performance of healthcare sectors in countries like Slovenia, Slovakia, Lithuania, Hungary, Greece, and Estonia. The development of best practices and resource planning in medically inefficient countries can also be inspired and learnt from medical processes in Spain, Austria, Germany, and Switzerland. Therefore, policymakers of inefficient countries must study these countries’ healthcare management policies and try to

Table 1 Descriptive statistics of input and output parameters

	Parameters								
Measures	Days of lockdown	Special package	Tests performed	Infected patients	Acute care beds	General beds	Doctors	Recovered patients	Deceased patients
Mean	37.15	71.55	323292.12	42663.85	696.97	93232.2	89008.12	14986.00	4427.42
Std. Dev	8.92	143.83	488898.53	66281.75	1038.03	145206	104768.39	29227.93	7974.57
Max	47.00	600.00	2072669.00	219764.00	4974.85	661448	351195.00	109800.00	25969.00
Min	28.00	0.10	37782.00	804.00	8.82	1052.00	1330.00	32.00	10.00
Range	19.00	599.90	2034887	21896	4966	660396	349865	109768	25959

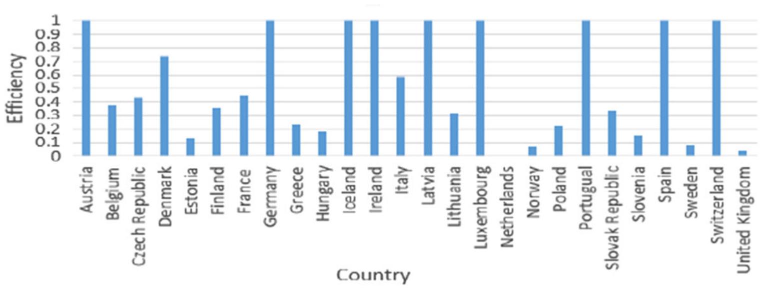


Fig. 6 Country-wise efficiency scores of OECD countries

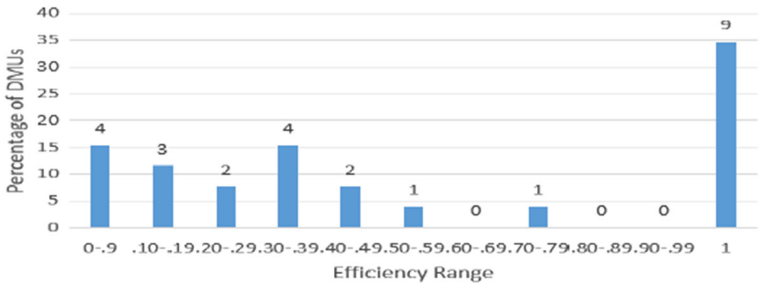
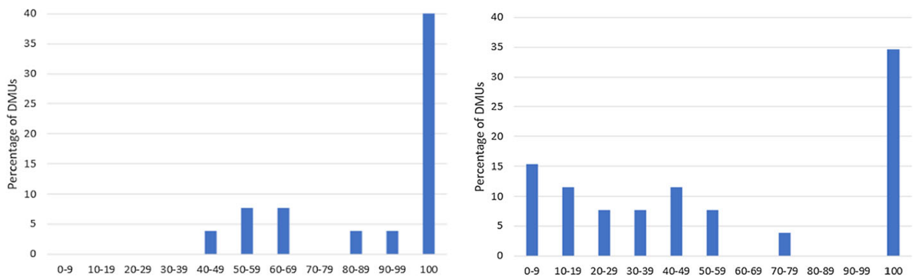


Fig. 7 Distribution of the overall efficiency of OECD countries



(a) Efficiency distribution of stage-1

(b) Efficiency distribution of stage-2

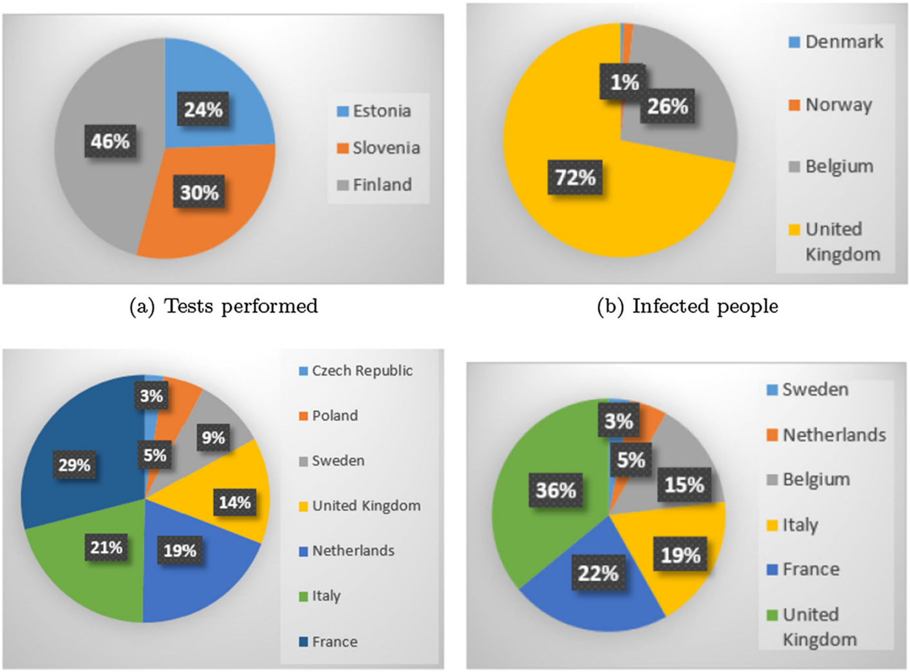
Fig. 8 Stage wise efficiency distribution

replicate those models in their respective contexts. The discrimination among the countries based on non-medical interventions is much less, which is perceived as a major area of strength in countries such as Lithuania, Poland, Germany, Hungary, Iceland, and Portugal.

The third column of Table 2 shows there are a total of 104, 475 extra infected people over and above the optimal number. Only four countries, namely Belgium, Denmark, Norway, and the UK, are accountable for this sub-optimality Fig. 9b. Among them, the UK caused 72% of the total surplus. This poor performance by the UK, Norway, Denmark, and Belgium can be partly justified by the unfavorable realisation of the demographic factors, which lead to 52% spike in the number of infected patients. The current condition of infected patients is 110% of the optimal condition. The two outputs, tests performed and infected people, are the outcome of non-medical activities (stage 1). An interesting finding is that the majority

Table 2 Descriptive statistics of inefficiencies in output parameters

Measures	No. of tests performed	Infected patients	Recovered Patients	Deceased Patients
Total	157568.6	104475.41	139961.2	41320.86
Average	6060.33	4018.29	5383.12	1589.26
Max	Finland	United Kingdom	France	United Kingdom
Non-Zero	3	4	16	15
Percentage	1.87	9.41	36	36



(a) Tests performed (b) Infected people

(c) Recovery rate (d) Mortality rate

Fig. 9 Major sources of inefficiency and country-wise distribution

of OECD countries performed well (see Fig. 8a) in stage 1, without large inequality among them (Mean = 0.9, SD = 0.17).

The number of recovered patients has a total deficiency of 139, 961, which is 36% of the total patients recovered overall. There are 16 countries, out of 26 which are classified as sub-optimal in this parameter. For example, France, Italy, Netherlands, and the UK collectively cause 77% of the total deficiency in recovery rate Fig. 9c. The total number of deceased patients surpass the optimal value by 41, 320, which is 36% of the total deceased patients. The number of total deceased patients is 156% of its optimal size. Fifteen countries experienced excessive fatality. Surprisingly, the majority of the excess fatality took place in the four worst-performing countries, namely Belgium, France, Italy, and the UK Fig. 9d. Note that the last two outputs are associated with the second stage. This leads to relatively low average efficiency, mean 0.54, and standard deviation 0.37 (see Fig. 8b). The average efficiency of

Table 3 Categorization of OECD countries

60+ age	Smokers	Health Exp	Countries
Good	Good	Good	Hungary, Iceland, Norway, Sweden
Good	Good	Bad	Austria, Belgium, Czech-Republic, Denmark, Estonia, Finland, Greece, Ireland, Latvia, Lithuania, Luxembourg, Portugal, Slovak-Republic, Slovenia, Switzerland
Bad	Bad	Bad	France, Germany, Italy, Poland, Spain, United Kingdom

medical units in OECD countries is significantly less ($p < 0.01$) than that of non-medical offices.

OECD countries face a range of limitations in available resources and some of them suffer from poor utilization. The effectiveness of each of the counter-measures and resources can be determined from the weights in the optimal solution of model (4). OECD countries, namely Belgium, the Czech Republic, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Portugal, France, Italy, Poland, and Slovakia put abundant restraints in the form of lockdown, and yet could not attain the expected levels of outcome. France is the only country to have operated acute care beds efficiently. Therefore, the rest of the countries can improve the final outputs of the second stage with higher utilization of acute care beds. Countries like the Netherlands, Ireland, Slovakia, Portugal, and Sweden faced shortages of general beds. Every hundred additional beds in these countries increase the recovery rate, on an average, by 4%. For countries like Italy, the UK, Germany, and Spain, this marginal benefit is only 0.35%. The remaining half of the countries have a sub-optimal allocation of general beds. General beds are, on average, more efficient than the number of doctors and acute care beds put together. Therefore, basic medical facilities appear to have delivered better results. These findings help nations to break the financial predicament by comparing the respective gains from different investment alternatives. For example, for France, the weights of the special financial aid (billion USD) and acute care beds (per million citizens) are .0027 and .00031, respectively. Therefore, in terms of the relative improvement in productivity, measured by a reduction in output shortage or excess bad output, an additional billion USD is nine ($.0027/.00031 = 9$) times more effective than additional acute care beds per million population.

5.1 Categorical DEA analysis

The results in section (3.1) indicate that OECD countries are facing different levels of unfavorable conditions that are beyond their control in a short time frame. The fundamental assumption of DEA is that the countries within a comparable environment should be evaluated against each other. Otherwise, evaluating a country in the most unfavorable condition with the ones in the most favorable condition would underrate the efficiency of the former. Therefore, to make the evaluation process realistic and implementable, the countries are classified into three possible categories based on the level of favoritism of each of the three externalities of the respective countries.

The second row of Table 3 depicts the best-case scenario where all three external factors assume favorable values. The third row signifies the second most favorable condition with small health expenditure. The last row lists the countries that face most unfavorable conditions in all three aspects. In categorical DEA, the last category is evaluated within itself. The second

Table 4 Categorized and Non-categorized efficiency of OECD countries

Category	Nation	Cat Eff	Non-Cat eff	Category	Nation	Cat Eff	Non-Cat eff
Best	Hungary	0.18	0.18	Good	Lithuania	0.45	0.32
Best	Iceland	1.00	1.00	Good	Luxembourg	1.00	1.00
Best	Norway	0.07	0.07	Good	Netherlands	0.00	0.00
Best	Sweden	0.07	0.07	Good	Portugal	1.00	1.00
Good	Austria	1.00	1.00	Good	Slovakia	1.00	0.33
Good	Belgium	0.39	0.37	Good	Slovenia	0.18	0.15
Good	Czechia	1.00	0.43	Good	Switzerland	1.00	1.00
Good	Denmark	0.74	0.71	Worst	France	0.55	0.44
Good	Estonia	0.56	0.13	Worst	Germany	1.00	1.00
Good	Finland	0.36	0.36	Worst	Italy	0.68	0.58
Good	Greece	0.26	0.23	Worst	Poland	1.00	0.22
Good	Ireland	1.00	1.00	Worst	Spain	1.00	1.00
Good	Latvia	1.00	1.00	Worst	The UK	1.00	0.04

last and the first category are evaluated within the last two categories and all three categories, respectively.

The most unfavorable category consisting of countries like France, Germany, etc., would not include countries from the rest of the categories into their peer groups. Hence, in categorized evaluation, these countries would improve on their efficiency scores. Table 4 shows categorical and non-categorical efficiency scores as "Cat eff" and "Non-Cat eff".

The same set of external factors might affect countries differently. For example, the UK has improved its efficiency from 0.04 to full efficiency. On the other hand, countries from the same category, e.g., France and Italy, have only improved from 0.44 and 0.58 to 0.55 and 0.68, respectively. Thus, such negative externalities have a much worse effect on the healthcare services in the UK than they have in France or Italy. The countries that are efficient in both the categorical and non-categorical approach, e.g., Spain and Germany, achieved full efficiency despite the obstacles.

5.2 Risk assessment

While the operational efficiency measures have implications for the mitigation of the risks to public health, countries are currently at different stages of the crisis. Therefore, an in-depth examination of the credible threats to the countries in light of their recent performance could assist the policymakers further to develop strategies proactively in the right direction. The probability distribution of the rate of spread for an outbreak like Covid-19 is difficult to anticipate, particularly in the presence of different external factors. In this context, the risk that the OECD countries are facing can best be explained in terms of their vulnerabilities against the rate of the spread of the virus vis-à-vis the preparedness of the respective authorities of the countries. The epidemiology literature has recognized three possible stages of a pandemic outbreak: Acceleration, Stability, and Deceleration (Anderson et al., 2004). To identify the stage a country is currently in, the trend in the daily cases (or cases per test) needs to be evaluated. The transmission speed (TS) is captured by the daily new cases (DC) per daily

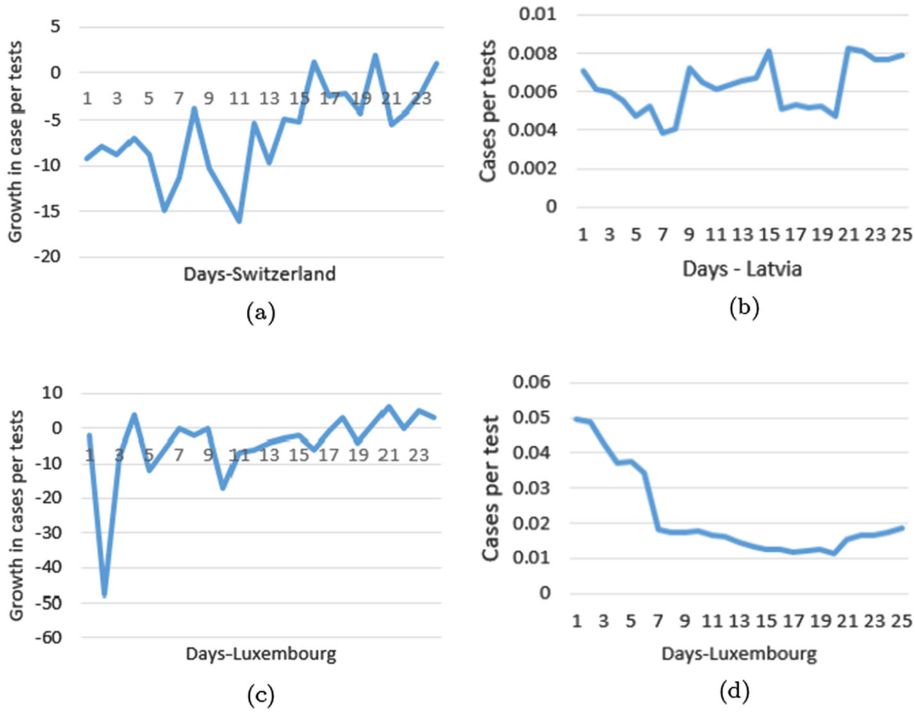


Fig. 10 Major sources of inefficiency and country-wise distribution

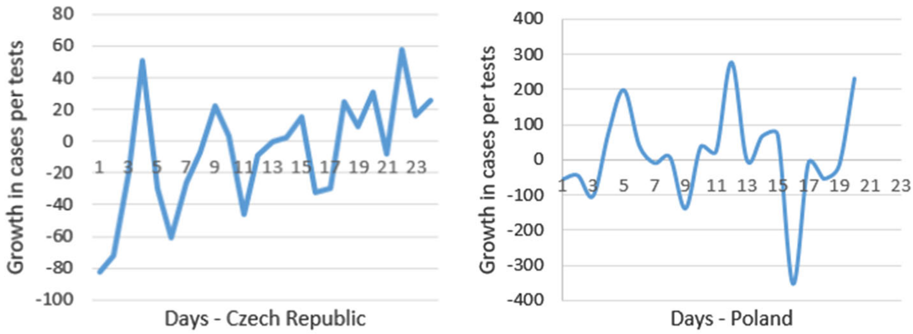
new testing (DT), $TS = \frac{DC}{DT}$. The slope in the graph of TS describes the acceleration in the spread.

However, the transmission speed gives a day-wise microscopic view of the transmission of the disease. A more stable and even measure that filters out daily noise would provide better monitoring of the transmission trend, especially in an exponentially changing scenario. We have used the moving average of the new cases for the last seven days, a rough estimate of the incubation period of Covid-19 (Lei et al., 2020). The seven-day moving average starts from 27-04-2020 that accounts for the TS_is from 21-04-2020 to 27-04-2020 and is denoted by MA_1, $MA_1 = \frac{\sum_{i=1}^{7} TS_i}{7}$. Similarly, $MA_2 = \frac{\sum_{i=2}^{8} TS_i}{7}$ accounts for the TSs of 22-04-2020 to 28-04-2020, and so on. The trend in the MA_ts helps one assess the rate of change of the spreading potential of the disease on a weekly basis.

Among the efficient countries, except for Latvia and Switzerland (see Fig. 10a), the rest have a downward sloping trend in infected people over the said period. Latvia observed mildly uneven growth in new cases per testing (see Fig. 10b). If the graphs are any indication of the future trends, the countries with decreasing daily cases per testing should aim at supporting societies and communities affected adversely by humanitarian crises.

The majority of the efficient countries have utilized the containment measures and health-care activities in tandem. The number of lockdown days is used in an efficient country three times more effectively than in an inefficient one. Similarly, financial aid in efficient countries, on average, has been twice more impactful than in inefficient countries.

The Czech Republic is in the high-risk zone, with an increasing trend in the number of daily cases (Fig. 11a). Moreover, it has the worst effects of lockdown and financial package



(a) Efficiency distribution of stage-1 (b) Efficiency distribution of stage-2

Fig. 11 Stage-wise efficiency distribution

(it is rated as the worst performer in both factors). So, this country is the one where the risk of the epidemic getting worse in the future is the highest.

Following a period of stable transmission, Luxembourg experienced an increase in transmission rate. The more concerning matter is that it ranks amongst the poorest performers in terms of productivity of lockdown days, the number of doctors and acute care beds. Considering the rising trend in Fig. 10c, d, the medical units around the country should be strengthened, while at the same time enforcing absolute compliance with the lockdown norms.

Poland faces similar threats (Fig. 11b), having performed poorly in medical care. Except for financial aid, it failed to properly utilize any of its input resources. The daily cases per daily tests have a slow trend of reduction. But the rate of change is very erratic. The healthcare units would come under heavy pressure during those spikes.

5.3 Coordination efforts

In recent years, the world has witnessed an increasing number of pandemics, such as SARS, Ebola, H1N1, among others, threatening the global health system. Despite that, governments around the world seem to lack the willingness and proper planning in order to establish an integrated healthcare system to combat any epidemic. Interdependent government agencies in different countries have conflicting opinions about the assessment of and response to pandemic situations (Kim & Kreps, 2020). To respond to the need for coordinated efforts from different organizations, e.g., medical units, disaster management agencies, safety, law enforcement departments, public health bodies, and local governments, the OECD countries took several initiatives for close coordination of these departments to counter the outbreak (Organisation for Economic Co-operation and Development, 2020). Starting from the identification of contacts to tracing them so as to list all the possible transmitted contacts of the infected person, synchronized data management has an important role to play in data management, information availability, spreading awareness, and risk assessment using real-time decision/expert support systems (He et al., 2021). Such steps involve encouraging telemedicine and the smarter use of data for surveillance and tracking, improving the affordability of diagnostics and treatment for all, and mobilizing and protecting health workers, among others. Table 5 exhibits the segmentation of the countries based on their approach towards these countermeasures.

Table 5 Technical efficiency results by countermeasures

Tracking Measure	Category	Country		Efficient		Inefficient		Efficiency Mean	Efficiency SD	p value
		N	%	N	%	N	%			
Surveillance & Tracking	Low	8	31	2	25	6	75	.42	.37	.16
	High	18	69	7	39	10	61	.57	.38	
Optimize Hospitals	Low	8	31	3	38	5	62	.50	.40	.37
	High	18	69	6	33	12	67	.54	.37	
Vaccine & Treatment	Low	14	54	2	14	12	86	.38	.29	.03
	High	12	46	7	59	5	41	.70	.39	
Affordable Diagnostic	Low	12	46	4	33	8	67	.52	.39	.4
	High	14	54	5	36	9	64	.53	.37	

The efficiencies of the countries encouraging telemedicine, the smarter use of data for surveillance, and tracking have improved with a mild significance ($p < 0.15$) (see Table 6), as compared to that of the rest of the countries. The majority of the countries have good insurance coverage of inpatient care, pharmaceuticals, and the cost of diagnosis. However, the countries with affordable diagnosis and treatment have significantly *better* recovery rates (ANOVA, $p <= 0.0000$) than the rest (refer to Table 6).

Having encountered a pandemic with an exponential growth rate, the international and provincials bodies "push" for a timely solution by accelerating R&D for vaccine and treatment. The average efficiency score of countries with accelerating R&D ($M : 0.70$, $SD : 0.39$) is *significantly* higher ($p < 0.05$) in comparison to the rest ($M : 0.37$, $SD : 0.29$). The Netherlands lacked in R&D in vaccine and treatment, and affordability of diagnostics and treatment. Norway lacked in the smart use of data for surveillance and tracking and optimization of beds and spaces in hospitals. On the other hand, Sweden lacked in all four areas. As a result, they all have experienced devastating medical calamities, resulting in a disproportionate amount of fatality and active cases.

6 Managerial implications

The findings of this study show how medical units (hospitals, critical care units, etc.) are overwhelmed in the initial phase of the pandemic. The results show that the medical outcome can be improved by almost 40%. Though certain groups of researchers pointed out the high number of infected people getting admitted to the hospital and thus overwhelming the existing healthcare services (Tangcharoensathien et al., 2021), it is clear that only around 10% inefficiency in terms of additional infected patients should not have resulted in 40% inefficiency in the patient outcome. As the UK's national health policy came under a lot of criticism for cutting down on funding and lack of quality in primary care, it became the largest source of infected people and patient fatalities, along with Belgium. This has happened primarily due to lean practices being adopted in the healthcare sector (Gold & Evans, 2020). The "big-four" countries primarily responsible for the huge number of infected people (Fig. 9b)) are partly impacted (52% of the total inefficiency) by the unfavorable realization of demographic factors. Thus, these countries need long-term strategic planning to neutralize the negative externalities and to help the victims get back to their 'normal' lives.

Table 6 Technical efficiency results by countermeasures

Tracking measure	Category	Infected person			Excess death			Recovery Shortage		
		Mean	%	SD	Mean	%	SD	Mean	%	SD
Surveillance & Tracking	Low	158	1.4	473	1012	22	2457	5329	30	9026
	High	5724	98.6	18K	1789	78	3927	5407	70	10373
Optimize Hospitals	Low	–	–	–	173	3.3	400	2583	17	4207
	High	–	–	–	2218	96.7	4108	6627	83	11442
Vaccine Treatment	Low	2292	26	7603	1252	74	2362	5910	60	88352292
	High	6412	74	20.7K	1981	26	4534	4768	40	11135
Affordable Diagnostic	Low	37	0.5	121	951	35	2086	6189	67	9593
	High	7431	99.5	20044	1505	65	3946	2558	33	4661

Relatively fewer infected people does not always translate into a lower fatality rate. Several countries, such as the Netherlands, Estonia, Finland, France, Poland, Slovakia, Norway, and Sweden, have sadly failed in attaining efficient medical records despite controlling the spread of the epidemic and keeping the infected count low. Surprisingly, these same countries have scored 55% to 70% on the scale of 100% completeness criteria defined in terms of the number of quality criteria completed as prescribed by the World Health Organization (Mounier-Jack & Coker, 2006). The nation-states should abide by the Schengen agreement to act collectively against any possible threat of a pandemic in compliance with the law (Martin, 2009). As the nation-states in the EU have porous boundaries, a harmonized approach toward public health and maintaining standard protocol is essential for the mitigation of the Covid-19 pandemic. In light of this, integration of digital technology, particularly in the non-medical interventions, into the disaster management and response systems amplifies the healthcare and disaster management capabilities such as planning, scheduling, surveillance, managing quarantine, and contact tracing (Whitelaw et al., 2020).

In order to measure the effectiveness of various digital technologies and healthcare preparedness, we have considered the use of 'Surveillance & Tracking', 'Optimizing hospitals', 'Vaccine & Treatment', and 'Affordable Diagnostics' in the containment of the pandemic. South Korea's successful implementation of IT infrastructure allowed them to have one-tenth of the total fatality rate compared to the United States while only having one-third of the hospital beds. Some of these factors are also causally linked to one another. Low affordability and higher out-of-pocket expenses, for example, discouraged people from having an early test, making the recovery of infected people even more difficult at a later stage of the infection. However, the high mortality rate in economically developed countries suggests that early detection does not always result in better recovery, which is influenced by a variety of factors such as average age, comorbidity issues, and so on.

Activities critical to the lifecycle of a disaster include preparedness, response, rehabilitation, and mitigation. Preparedness refers to the measures put in place to effectively deal with any future crisis situation (Goldschmidt & Kumar, 2016). The response phase addresses the ongoing crises by allocating appropriate resources and implementing effective planning in order to save human lives, the economy, etc. During the rehabilitation and mitigation phases, actions are taken to stabilize the situation in the long run and restore normalcy, as well as to lessen the immediate negative impact of the disaster, respectively. In the proposed framework, stage-1 addresses the first two critical activities: preparedness and response. Stage-2 is directly responsible for rehabilitation and mitigation.

According to both epidemiology and disaster management literature, efficient utilization of available resources is one of the critical success factors in mitigating the final loss for two primary reasons. Firstly, the mobilization of medical supplies and disaster relief materials in the affected regions is difficult. Secondly, any underutilized resources cause an inevitable loss of human lives or property. The efficiency of nation-states in utilizing available resources is examined using DEA. Thus, this study has strong implications for the theorists in Operations Research and Disaster Management area.

The theorem and the underlying lemmas show that overall efficiency is not possible unless stage-wise efficiencies are achieved. The degree of coordination among different units or departments can now be put under scrutiny and also the conflict between different departments (health services, disaster management, local administration, etc.) functioning as different stages in the overall process can be quantified and resolved. Because of the segregation of inputs and outputs among different stages, the measurement of an input's utilization in producing a particular output becomes more accurate and relevant. In the 'black-box' approach with only one stage, all the inputs and outputs would have been merged, which leads to inaccurate assumptions. For example, the number of doctors, beds, etc., should not have any influence on the number of tests done. Another important result follows directly from lemma 3.2., that in the overall process there might not be any efficient countries. In the conventional DEA technique, some DMUs are bound to be efficient, particularly under the VRS assumption, irrespective of how small or large slack and surplus values are embedded in their operating model. In other words, the result implies that each country can learn from some other countries to improve its performance in some stages.

7 Conclusion

The performance assessment of the OECD countries in response to the pandemic is timely and helpful to the global community of academics and researchers. The contribution of this study is not only to its application in healthcare but to the broader literature on NDEA. The study identifies the areas of improvement for social measures and medical services in OECD countries. The improved efficiency of the countries has implications for any future pandemics or natural disasters. The relevant DEA framework includes the links (the intermediate measures) between the two stages that play an important role in a synchronised mechanism to control the disease. The comparative analysis of externalities, e.g., health expenditure and the proportion of senior citizens, influencing the outcome of the countries' countermeasures can be used to infer broader conclusions involving policy frameworks at national levels.

The study of infected patients as an undesirable intermediate measure explores the interdependency between two processes, namely, Public Administration and Hospital Authorities. Theoretically, this work adds to the ever-growing literature on NDEA by proposing the concept of maximizing the reduction in intermediate measures jointly by the two stages. This avoids the classical dilemma of a generic two-stage system in NDEA to determine whether to increase or to reduce the intermediate measures. This study also highlights how a disjointed approach by the two sectors puts insurmountable pressure on the medical units, causing a high mortality rate.

The huge disparity in performance between top and bottom performers is most evident in terms of mortality and recovery rates. The primary reason for this is identified to be the number of general beds by interpreting the shadow prices of medical resources. Therefore, the inefficient countries must learn best practices from Iceland, Austria, Germany, etc., and develop improvements in the areas of their weaknesses in medical care.

Several other factors that influence the spread of Covid-19 and the fatality rate, such as population density, the co-morbidity percentage, etc., are not included in the study due to the unavailability of the data. With a wide variety of mathematical modelling used in the field of epidemiology, this paper leads to the opening up of further scopes in modelling, e.g., allocation of shared resources, stochastic analysis, etc. One might also explore the idea of sharing resources of "non-rival" nature, such as public goods, among the nations from a co-operative game-theory perspective. In the current framework, the two-stage series network can be replaced with complex network structures to model real-time disaster management systems where multiple agencies are interlinked. This might disclose interesting insights about the nature of interactions among the stages and highlight the trade-offs in the services provided by the stages. However, one limitation of this study is that micro-level healthcare data are aggregated to be considered in national (macro-level) studies. The economic and social factors and the welfare of public health in the ongoing pandemic are very fragile.

Therefore, more stable conditions within the OECD countries would bring more consistency and reliability to the empirical analysis.

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