sustainability

Article

Efficiency Assessment of Operations Strategy Matrix in Healthcare Systems of US States Amid COVID-19: Implications for Sustainable Development Goals

Aydın Özdemir [1,2,*], Hakan Kitapçı [1], Mehmet Şahin Gök [1] and Erşan Ciğerim [1]

[1] Department of Management, Faculty of Business Administration, Gebze Technical University, Kocaeli 41400, Turkey; kitapci@gtu.edu.tr (H.K.); sahingok@gtu.edu.tr (M.Ş.G.); cigerim@gtu.edu.tr (E.C.)
[2] Besni Ali Erdemoğlu Vocational High School, Adiyaman University, Adiyaman 02300, Turkey
* Correspondence: aydinozdemir17@gmail.com

Citation: Özdemir, A.; Kitapçı, H.; Gök, M.Ş.; Ciğerim, E. Efficiency Assessment of Operations Strategy Matrix in Healthcare Systems of US States Amid COVID-19: Implications for Sustainable Development Goals. *Sustainability* **2021**, *13*, 11934. https://doi.org/10.3390/su132111934

Academic Editors: Golam Kabir, Sanjoy Kumar Paul and Syed Mithun Ali

Received: 1 September 2021
Accepted: 20 October 2021
Published: 28 October 2021

Abstract: The objective of this study is to assess the efficiency of the operations strategy matrix in the healthcare system of U.S. states amid COVID-19. Output-Oriented Data Envelopment Analysis was used to assess the efficiency of the operations strategy matrix. Strategic Decision Areas (Capacity, Supply Network, Process Technology, and Development and Organization) were considered inputs while competitive priorities (Quality, Cost, Delivery, and Flexibility) were considered outputs. According to results; Alaska, Alabama, Arkansans, Florida, Hawaii, Iowa, Idaho, Louisiana, Minnesota, Missouri, Mississippi, Montana, North Carolina, New Jersey, New York, Oklahoma, South Carolina, South Dakota, Texas, Vermont, Wisconsin, and Wyoming are relatively efficient. Additionally, Connecticut, Louisiana, Minnesota, New Jersey, Rhode Island, Tennessee, Utah, Vermont, Washington, and Wyoming are fully efficient while South Dakota is the state that needs the most improvement in terms of strategic decision areas and competing priorities. On the other hand, inefficient states have larger population and GDP than efficient states. Based on these results, implications for sustainable development goals (SDGs) are drawn.

Keywords: efficiency assessment; operations strategy matrix; data envelopment analysis; healthcare systems; COVID-19

1. Introduction

A novel coronavirus named COVID-19 was identified in Wuhan/China on 31 December 2019, and the World Health Organization (WHO) assessed that COVID-19 could be characterized as a pandemic on 11 March 2020. The first case was confirmed on 22 January 2020 and as of 27 June 2021, due to COVID-19, there were 34,494,677 confirmed cases and 619,424 confirmed deaths in the USA [1].

Centers for Disease Control and Prevention (CDC), a service organization that protects the public's health, has prepared a global response to COVID-19. It includes the goals limiting human-to-human transmission, minimizing the impact of COVID-19 in some states with limited healthcare delivery capacity, and reducing certain threats that pose a risk to the United States' healthcare system [2]. In this context, public health, and social measures have been implemented to prepare and respond to the pandemic [3]. Although there have been many actions implemented to cope with the pandemic, the increasing number of COVID-19 cases poses a major threat to healthcare delivery [4].

WHO has provided comprehensive guidance to community and service providers to minimize the spread of the disease [5]. Since the early experience shows that COVID-19 requires unprecedented mobilization of health systems, it is recommended to assess the health systems to mitigate the outbreak's impact [6].

Although health is only one of the UN Sustainable Development Goals (SDGs), many other health-related goals comprise determinants of health [7]. The SDGs represent a unique opportunity to promote and assess public health [8]. The healthcare assessment process seeks to measure how care affects individuals or populations' health and well-being [9]. The assessment is also vital for achieving the SDGs, especially Goal 3, described as ensuring healthy lives and promoting well-being for all at all ages [10]. because sustainability is a managerial trend that plays an important role [11], and implications drawn based on healthcare assessment help to help policymakers for favorable policymaking [12]. Mentioned assessment depends on the development of standards [13]. There are some standards and tools for assessing healthcare systems such as effectiveness, efficiency, humanity, and equity [14]. As a novel evaluation tool, Operations Strategy Matrix describes the operations strategy as the intersections of an organization's performance objectives (competitive priorities) with its decision areas [15]. According to Slack and Lewis (2017); the matrix can be considered a checklist of the issues required to be assessed and helps operations to be extensive. Additionally, all intersections on the matrix don't have equal importance. Some intersections are more critical than others. This depends on the nature of operations. The matrix has four strategic decision areas (capacity, supply network, process technology, and development and organization), and four competitive priorities (quality, cost, delivery, and flexibility) [15].

The research question of this study is as follows: are US states efficient in the healthcare system amid the COVID-19 pandemic, and how do the efficient or inefficient conditions affect Sustainable Development Goals (SDGs).

The objective of this study is (i) to assess the efficiency of the operations strategy matrix in the healthcare system of US states amid COVID-19. For this purpose, 50 US states were considered as Decision Making Unit (DMU), and output-orientated Data Envelopment Analysis (DEA) was used; and (ii) to draw implications for sustainable development goals (SDGs) based on DEA results. The unique contribution of this study lies in the use of the Operations Strategy Matrix to assess the healthcare system of US states and to draw the implications for Sustainable Development Goals (SDGs). To validate the Operations Strategy Matrix, Data Envelopment Model was used.

The research paper is organized as follows. The following section presents the exiting literature review associated with COVID-19 and the healthcare system. Section 3 describes the DEA methodology. Section 4 presents the results. Section 5 discusses the findings and draws implications for sustainable development goals (SDGs). The final section portrays the conclusion and opportunities for future work.

2. Related Research

The section presents the existing literature about COVID-19 and the healthcare system.

O'Leary et al. (2021) have documented the healthcare policies developed during the initial wave of widespread COVID-19 transmission in Ireland, and they have developed six category headings to describe to focus VOVID-19 policies: (i) infection prevention and control, (ii) residential care settings, (iii) maintaining non-COVID-19 healthcare services, and supports, (iv) testing and contact tracing, (v) guidance for healthcare workers concerning COVID-19, and (vi) treating COVID-19 [16]. Tsai and Yang (2020) have examined the impact of the COVID 19 outbreak on voluntary demand for non COVID-19 healthcare, and their research has indicated a substantial decline in healthcare use is caused by the prevention of measures for COVID-19 [17]. Adwibowo (2020) has recorded the daily COVID-19 cases and has continued with the forecasting of the average daily demand (ADD) of healthcare facilities including beds, ICUs, and ventilators using the ARIMA model, and the model has shown that the healthcare ADD is different in each population [18]. Alshammari et al. (2021) have evaluated the potentiality of emerging technologies for controlling the COVID-19 transmission and ensuring health safety and their study has revealed that most people receive information from social networking sites, health professionals, and television without facing any challenges [19]. Brodie et al. (2021) have explored how adopting a service ecosystem perspective provides insight into the complexity of healthcare systems during times of COVID-19, and they have provided an understanding of the relevance of managerial flexibility, innovation, learning, and knowledge sharing [20]. Arlotti and Ranci (2021) have argued that the negative impact of COVID-19 stems from the poor development of long-term care policy and the marginality of residential institutions within the Italian healthcare system [21]. Rodríguez and Hignett (2021) have presented a model for integrating Human Factors/Ergonomics into healthcare systems to make them more robust and resilient during the COVID-19 pandemic, and they have argued that it is crucial to have a systems vision focused on optimizing the interactions people and other healthcare systems elements [22]. Akiyama et al. (2020) have described how their experience with inpatient care has changed in the wake of COVID-19 and they have determined that COVID-19 hospital discharge rates surpass admission rates [23]. Tasri and Tasri (2020) have analyzed the competency influence of medical records and health information management on the planning and decision making of healthcare services, and they have concluded that the new tools or systems can be an alternative to improve healthcare management [24]. Bel et al. (2021) have built a theoretical model and used it to develop an empirical strategy, analyzing the drivers of policy-response agility during the outbreak, and according to their model, healthcare system capacity and cost-related variables have a significant influence on reaction time; therefore, this situation has negatively affected government strategy [25]. Chamboredon et al. (2020) have presented a brief history of the development of the pandemic in France, including the political decisions that have been taken to combat the outbreak, and they have argued that the history of the development of the pandemic helps explain the establishment of the state of health emergency and containment of the population. [26]. Leite et al. (2020) have evaluated the impact of the COVID-19 pandemic on healthcare systems' demand, resources, and capacity. Then they have discussed that the sustainability of lean post-pandemics is a new modern operational issue [27].

Currently, the world is facing a global health crisis COVID-19; however, ensuring healthy lives and promoting well-being at all ages is essential to sustainable development, and the pandemic provides a milestone for health emergency preparedness and investment in critical 21st-century public services [28]. The SDGs aim to be relevant to all countries to promote prosperity, and almost all of the other 16 goals are related to health, or their achievement will contribute to health implicitly [29]. The SDGs are a tremendous opportunity to improve the health of the people of the world, and to make progress on the SDGs, states/countries must invest more heavily in health services research [30]. To meet the SDG targets and improve health system quality, states/countries need to undertake a measurement agenda [31]. Measuring and assessing the efficiency of health systems has been explored to ensure the sustainability of countries'/states' health and social systems [32]. Furthermore, gaps in the efficiency of the healthcare system will interrupt achieving SDGs [33].

All of these research findings reveal that there is a close relationship between the efficiency of the healthcare system and the implications for sustainable development goals amid the COVID-19 pandemic.

3. Materials and Methods

3.1. Background of Data Envelopment Analysis (DEA)

DEA is a nonparametric method of evaluating the relative efficiency of DMUs that use the same inputs to produce the same outputs, such as firms or public sector agencies [34–36]. DEA is widely used in many areas such as healthcare, banking, education, auditing, market research, and agriculture [37–40].

DEA has been used as a benchmarking and assessment tool in healthcare worldwide [21]. In addition, DEA is considered one of the most effective techniques for relative efficiency assessments, as it can evaluate multiple inputs and outputs simultaneously [22]. According to Ozcan (2009), since it is a multi-dimensional construct, the assessment of efficiency is often troublesome. Nevertheless, DEA addresses the limitations of ratio analysis and regression. Additionally, DEA uses multiple outputs and multiple inputs to identify efficiencies and inefficiencies and also to project how inefficient DMUs can become more efficient, by identifying reference sets (best practices). A reference set function can be built from observed inputs and outputs [23].

DEA models can be divided into two main types; constant returns to scale (CRS), also known as CCR (Charnes-Cooper-Rhodes) model, was initially introduced by Charnes et al. in 1978 [41], and variable returns to scale (VRS), also known as BCC (Banker-Charnes-Cooper) model, was later developed by Banker et al. in 1984 [42]. While the CCR (CRS) model yields an objective assessment of overall efficiency, identifies the sources, and estimates the number of inefficiencies in this way, the BCC (VRS) model distinguishes between technical and scale inefficiencies by estimating pure technical efficiency and identifying possible increasing, decreasing, or constant returns to scale [20]. Unlike CCR (CRS) models, input and output efficiency are equal, BCC (VRS) models yield different input and output efficiencies [21]. In addition, while CCR (CRS) models can assume that economies of scale don't change as the size of service facility increases, BCC (VRS) models cannot assume that economies of scale don't change as the size of service facility increases [26].

DEA models can be either input-orientated or output-orientated. In the input-orientated case, the DEA method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held fixed for each DMU; in the output orientated case, the DEA method seeks the maximum proportional increase in output production, with input levels held constant for each DMU [43,44].

There are four DEA model classifications, also known as Basic Envelopment Models: CCR (CRS)-Input Orientation, CCR (CRS)-Output Orientation, BCC (VRS)-Input Orientation, and BCC (VRS)-Output Orientation [26].

The BCC (VRS) efficiency scores are considered pure technical efficiency scores, while CCR (CRS) efficiency scores are considered technical efficiency scores. On the other hand, scale efficiency can be calculated by dividing CCR (CRS) efficiency scores by BCC (VRS) efficiency scores [28].

The efficiency of each DMU is evaluated relative to optimal production patterns, which are computed from the performance of DMUs with input and output combinations that are the best of any peer DMU [40]. These evaluations result in an efficiency score that represents the degree of efficiency [45]. When the efficiency score for each DMU is a score of 1, it represents efficiency [40]. While DMUs with an efficiency score ranging from zero to one are defined as inefficient in the input-oriented models, DMUs with an efficiency score greater than 1 are defined as inefficient in the output-oriented models [43]. Once the efficiency frontier is set, the performance of inefficient DMUs can be improved by increasing the outputs quantities or decreasing the inputs quantities [46]. For this purpose, a reference set, also known as best practices, is identified for each inefficient DMUs [40,43].

According to Ozcan (2014), the performance of DMUs can be assessed either as fully efficient or weakly efficient. If one DMU's efficiency score is 1 and slack values (both input slack and outputs slacks) are 0, it is considered fully efficient [26]. On the other hand, while the slack value in an input "i" represents an additional inefficient use of input "i", the slack value in an output "r" represents an additional inefficient in the production of output "r" [21].

The basic efficiency measure is the ratio of total outputs to total inputs [17,21]. The mathematical structure and formulations of Basic Envelopment Models can be found in the studies of Cooper et al. (2006), Ozcan (2014), and Emrouznejad and Cabanda (2014) [20,22,24].

3.2. Sample

DMUs used in this study consist of 50 US states. The correct selection of DMUs to be compared is essential and DMUs should be homogeneous. In other words, DMUs should be performing the same tasks with similar objectives using the same inputs and outputs under the same set of market conditions [47]. The sample size is expected to be at least 2 or 3 times larger than the sum of the number of inputs and outputs [34]. This requirement was met, as the study has 50 DMUs, 4 inputs, and 4 outputs. Descriptive statistics of the sample are presented in Table 1.

Table 1. Descriptive statistics of the sample.

DMU	Population	GDP (2021 1st Quarter—$)	Region
Alaska (AK)	731,545	54,629	Far West
Alabama (AL)	4,903,185	238,726	Southeast
Arkansas (AR)	3,017,804	137,312	Southeast
Arizona (AZ)	7,278,717	394,490	Southwest
California (CA)	39,512,223	3,237,389	Far West
Colorado (CO)	5,758,736	413,578	Rocky Mountain
Connecticut (CT)	3,565,287	294,546	New England
Delaware (DE)	973,764	79,124	Mideast
Florida (FL)	21,477,737	1,151,608	Southeast
Georgia (GA)	10,617,423	653,938	Southeast
Hawaii (HI)	1,415,872	92,541	Far West
Iowa (IA)	3,155,070	205,694	Plains
Idaho (ID)	1,787,065	89,826	Rocky Mountain
Illinois (IL)	12,671,821	909,487	Great Lakes
Indiana (IN)	6,732,219	397,134	Great Lakes
Kansas (KS)	2,913,314	184,184	Plains
Kentucky (KY)	4,467,673	222,880	Southeast
Louisiana (LA)	4,648,794	257,593	Southeast
Massachusetts (MA)	6,892,503	611,917	New England
Maryland (MD)	6,045,680	442,858	Mideast
Maine (ME)	1,344,212	69,409	New England
Michigan (MI)	9,986,857	542,566	Great Lakes
Minnesota (MN)	5,639,632	396,994	Plains
Missouri (MO)	6,137,428	340,144	Plains
Mississippi (MS)	2,976,149	122,015	Southeast
Montana (MT)	1,068,778	55,107	Rocky Mountain
North Carolina (NC)	10,488,084	619,595	Southeast
North Dakota (ND)	762,062	58,777	Plains
Nebraska (NE)	1,934,408	137,268	Plains
New Hampshire (NH)	1,359,711	89,605	New England
New Jersey (NJ)	8,882,190	649,829	Mideast
New Mexico (NM)	2,096,829	106,380	Southwest
Nevada (NV)	3,080,156	185,163	Far West
New York (NY)	19,453,561	1,758,071	Mideast
Ohio (OH)	11,689,100	713,507	Great Lakes
Oklahoma (OK)	3,956,971	198,008	Southwest
Oregon (OR)	4,217,737	262,587	Far West
Pennsylvania (PA)	12,801,989	821,117	Mideast
Rhode Island (RI)	1,059,361	63,053	New England
South Carolina (SC)	5,148,714	255,468	Southeast
South Dakota (SD)	884,659	58,878	Plains

Table 1. *Cont.*

DMU	Population	GDP (2021 1st Quarter—$)	Region
Tennessee (TN)	6,829,174	386,444	Southeast
Texas (TX)	28,995,881	1,879,785	Southwest
Utah (UT)	3,205,958	209,203	Rocky Mountain
Virginia (VA)	8,535,519	579,860	Southeast
Vermont (VT)	623,989	34,565	New England
Washington (WA)	7,614,893	651,107	Far West
Wisconsin (WI)	5,822,434	357,365	Great Lakes
West Virginia (WV)	1,792,147	79,690	Southeast
Wyoming (WY)	578,759	39,061	Rocky Mountain

In this table, population data were provided from CovidActNow [48], and gross domestic product (GDP) and region data were provided Bureau of Economic Analysis (BEA) [49].

3.3. Inputs, Outputs, and Data

Since the input-output combination preferred by DMUs should produce an output bundle from the input bundle, it should be technically feasible [35]. In these bundles, both good (desirable) and bad (undesirable) inputs and outputs factors may be available [24]. When evaluating DMUs' efficiency, the desirable and undesirable factors should be addressed differently. Because in the standard DEA model, increases in undesirable inputs and desirable outputs are allowed, similarly, decreases in undesirable outputs and desirable inputs are allowed [50].

The operations strategy matrix mentioned earlier was used as the primary measurement tool.

Data used for inputs and outputs were collected from many databases, public and private agencies, web pages, etc. in the US for 17 months (from 22 January 2020 to 27 June 2021). The data source of each input and output is mentioned in its description.

There are four inputs used in the analysis; these are Decision Areas/Strategic Decision Areas in the Operations Strategy Matrix adapted from Slack and Lewis (2017) and Karuppan et al. (2016) as the main input framework [15,51].

Capacity (i1): An operation's capacity is the maximum level of value-added activity that it can perform under normal conditions [15]. Capacity measures can be based on outputs or the availability of inputs [52]. Most healthcare facilities' capacity indicators are composed of volume measures per reporting period [53]. The capacity of healthcare systems is determined by the capacity of each server and the number of servers being used [40]. According to the CDC, as an essential disease control measure used by local and state health department personnel for decades, contact tracing is a key strategy for preventing the further spread of COVID-19. Thus, it requires people with the training [54]. On the other hand, Donabedian's Model has argued that personnel is an input measure of healthcare quality [13]. The Capacity, therefore, is represented by the "Contact Tracer Capacity Ratio" in this study. Data were provided from CovidActNow [48].

Supply Network (i2): Since a supply network perspective is defined as setting an operation with all the other operations, it interacts with materials, parts, ideas, information, data, knowledge, and people all flow through the supply network formed by all these operations [55]. The Supply network involves the design and management of seamless inter and intra-organizational processes [39]. Moreover, material, information, and capital flows must be sustainable [40]. However, COVID-19 has created trouble to manage a sufficient supply network [41]. Since COVID-19 vaccines reduce the risk of people spreading the virus, vaccinations are vital to get population immunity [56–59]. COVID-19 vaccines and ancillary supplies are procured and distributed by the US federal government at no cost to jurisdictions (states, territories, tribes, and local entities) [60,61]. The transportation ecosystem provides the technologies, services, and processes necessary to facilitate market penetration [44]. According to CDC, distribution is the process of shipping vaccines to provider locations, as directed by jurisdictions, federal agencies, and pharmacy partners who are enrolled in the COVID-19 Vaccination Program. Vaccine delivery is the last part of the distribution process. Deliveries represent the vaccine doses that have arrived at their destination [62]. The Supply Network, therefore, is represented by the "Distributed Vaccine Amount/Per Capita" in this study. Data were provided from CovidActNow [48].

Process Technology (i3): Process technology refers to the machines, devices, and equipment that create and deliver products and services [55]. Process technologies can be classified into three types: material processing technologies such as flexible manufacturing systems, information processing technologies such as optical character-recognition machines, and customer processing technologies such as medical equipment/devices [15]. The successful delivery of health care depends on medical devices; therefore, the Management of Medical Equipment (MME) is considered the most critical component within Health Systems [63]. The SEIR model attempts to predict how a disease will evolve in a population. Accordingly, all of the COVID-19 deaths have progressed from ICU cases [64]. On the other hand, Donabedian's Model has argued that facilities and equipment are input healthcare quality measures [13]. The Process Technology, therefore, is represented by the "Intensive Care Unit (ICU) Bed Capacity/Per 100,000 Population" in this study. Data were provided from CovidActNow [48].

Development and Organization (i4): This input is concerned with a broad and long-term set of decisions governing how the operation is run continuingly due to different employees having different tolerance for risk and ambiguity [15]. Additionally, it includes the workforce organization, planning and control, and improvement activities as an infrastructural decision [55]. Since COVID-19 has swept across the USA, it became clear that certain factors—such as healthcare systems—make some states more vulnerable to its impact [65]. Vulnerability is a state of sensitivity to disaster [66]. States with higher vulnerability have pre-existing economic, social, and physical conditions that may make it hard to respond to the COVID-19 outbreak [67]. According to Surgo Ventures, the COVID-19 Community Vulnerability Index (CCVI), developed by Surgo Ventures, evaluates how well any state could respond to the health, economic and social consequences of COVID-19 without appropriate response and additional support. It ranges from 0 to 100 and constitutes seven themes: Socioeconomic Status, Minority Status & Language, Household & Transportation, Epidemiological Factors, Healthcare Systems Factors, High-Risk Environments, and Population Density. Theme 5, Healthcare System Factors, measure the capacity, strength, accessibility, and preparedness of the healthcare system to respond to the COVID-19 outbreak [68]. Development and Organization, therefore, is represented by the "The COVID-19 Community Vulnerability Index (Theme 5: Healthcare System Factors)" in this study. Data were provided from Surgo Ventures (Precision for COVID) [68].

There are four outputs, two of which undesirable output, used in the analysis: these are Competitive Priorities or Performance Objectives in the Operations Strategy Matrix adapted from Slack and Lewis (2017) and Karuppan et al. (2016) as the main output framework [15,51].

Quality (o1): Since quality usually means the high specification of a product or service [15], it can be defined as consistent conformance to customers' expectations [15,55]. Because quality has two dimensions, high-performance design and, goods and services consistency [69], in the healthcare area, quality means that patients receive the most appropriate treatment and that their treatment is carried out correctly [55]. Adopting the most effective prevention and treatment practices for the leading causes of mortality, and enabling healthy living are healthcare systems' priorities [51]. On the other hand, Donabedian's Model has argued that patient experience, restoration of function, recovery, and survival are the output measure of healthcare quality [13]. Therefore, as an undesirable output, Quality, is represented by the "Deaths/1M Population" in this study. Data were provided from Worldometers [1].

Cost (o2): As a competitive priority, cost means offering a product or a service at a low price relative to the substitute's product or service prices [69]. Even organizations that compete on things other than price are interested in keeping their costs low [15]. Economic efficiency considers whether a given output is produced at a low cost [13]. In the healthcare area, the total cost includes the costs of resources such as material, equipment, people, facilities, and the costs inherent in the transformation process [51]. According to USASpending.Gov; in early 2020, the U.S. Congress appropriated funds in response to the COVID-19 pandemic. These funds were made possible through the Coronavirus Aid, Relief, and Economic Security (CARES) Act and other supplemental legislation. In March 2021, additional funds were appropriated through the American Rescue Plan Act. Once the federal government has determined that an individual, organization, business, or state, local, or tribal government will receive an award, the money is obligated (promised) and then outlay (paid) according to the terms of the contract or financial assistance [70]. Therefore, as an undesirable output, the cost is represented by the "Award Outlays/Per Capita Spending" in this study. Data were provided from USASpending.Gov [70].

Delivery (o3): Delivery, as a competitive priority, refers to the ability to provide services on time (on-time delivery) or to deliver the services faster (rapid delivery) than the competitors [51]. Rapid delivery means how quickly an order is received, while on-time delivery means how often deliveries are made on time [69]. Healthcare delivery includes many repetitious workflows, such as filling prescriptions, reporting laboratory test results, and completing radiology images [71]. Donabedian's Model has argued that preventive management, coordination, and continuity of care, acceptability of care to the recipient are the process measure of healthcare quality [13]. Immunization with a safe and effective COVID-19 vaccine is a critical component of the United States strategy to reduce COVID-19-related conditions [60]. Vaccines are widely accessible in the United States and are available for everyone at no cost [59]. Percent vaccinated is the percentage of the total population of a state that has started the vaccination process by receiving at least their first dose [67]. Therefore, delivery is represented by the "Vaccinated Rate (+1 Dose)" in this study. Data were provided from CovidActNow [48].

Flexibility (o4): Flexibility means being able to change the operation anywise [55]. Competing on flexibility refers to responding to changes with minimal penalties [51]. One operation that can exhibit a wide range of abilities is more flexible than another [15]. As customer demand is increasing, organizations are increasingly promoting different models of their products and service [72]. A flexible system can rapidly increase or decrease the quantity of production to meet demand fluctuations [69]. Some operational uncertainties can be balanced by systematic flexibility [73]. In the healthcare area, excess capacity or a flexible workforce is often required to meet demand fluctuations [52]. An essential metric for coping with demand fluctuations caused by COVID-19 is whether hospitals can handle the increased load of new COVID-19 cases without resorting to crisis standards of care [64]. Flexibility, therefore, is represented by the "Available ICU Capacity (by percentage)" in this study. Data were provided from CovidActNow [48].

According to the explanations above, it is assumed that the input bundle used by DMUs can produce the output bundle in the Operations Strategy Matrix.

Summary statistics of inputs and outputs are presented in Table 2.

Table 2. Summary statistics of inputs and outputs.

Inputs	Min.	Max.	Mean
Capacity (i1)	0.200	8.5700	1.8162
Supply Network (i2)	0.8705	1.4739	1.1311
Process Technology (i3)	14.25	41.10	25.38
Development and Organization (i4)	0.0000	1.0000	0.5212
Quality (o1)	364	2976	1692
Cost (o2)	2316	25,947	4063
Delivery (o3)	0.3590	0.7350	0.5244
Flexibility (o4)	0.1800	0.6000	0.3368

3.4. Analysis Design

The analysis consists of two stages. In the first stage; since there are two undesirable (bad) outputs in the dataset, BCC (VRS)-Output Orientation DEA model was employed in this study. The model proposed by Seiford and Zhu (2002) was applied for undesirable outputs [50]. Then, DMUs were evaluated using pure technical efficiency scores, a reference set was identified for each inefficient DMUs, and improvement options of inefficient DMUs were calculated. In addition to this, fully efficient DMUs are determined based on efficiency scores and slack values. All analyses were performed using the deaR package in the R project [74].

In the second stage; an independent-samples *t*-test was conducted to compare DMUs' populations in the efficiency and inefficient conditions and an independent-samples *t*-test was conducted to compare DMUs' gross domestic product (GDP) in the efficiency and inefficient conditions.

4. Results

Pure technical efficiency scores and inputs/outputs values of US states are shown in Table 3.

Table 3. Pure technical efficiency scores and input/output values.

DMU	Efficiency Score	i1	i2	i3	i4	o1	o2	o3	o4
Alaska	1	1.64	1.1338	17.50	0.24	502.00	6287.97	0.484	0.27
Alabama	1.01025	0.44	0.9793	33.37	0.96	2312.00	2655.36	0.394	0.18
Arkansas	1	0.54	0.9400	32.18	0.70	1953.00	2316.43	0.416	0.29
Arizona	1	0.16	1.1121	30.36	0.82	2461.00	2695.86	0.492	0.50
California	1.01127	2.09	1.2408	17.58	0.90	1609.00	3544.20	0.608	0.31
Colorado	1.00959	0.62	1.2188	22.21	0.44	1211.00	3741.60	0.576	0.30
Connecticut	1	2.65	1.3218	29.51	0.12	2321.00	3701.11	0.666	0.51
Delaware	1.03175	2.29	1.3115	19.51	0.10	1740.00	4226.13	0.577	0.25
Florida	1.00605	0.33	1.1561	29.71	0.92	1759.00	3190.01	0.531	0.25
Georgia	1.06975	0.97	1.0511	26.01	0.98	2015.00	3963.08	0.425	0.25
Hawaii	1	1.48	1.3699	15.33	0.28	364.00	4628.79	0.694	0.42
Iowa	1.02645	1.18	1.0937	21.39	0.52	1943.00	3253.92	0.512	0.34
Idaho	1	0.51	0.9325	17.18	0.38	1200.00	3009.66	0.393	0.35
Illinois	1.04749	3.09	1.1558	26.52	0.88	2023.00	4596.03	0.588	0.40
Indiana	1.01591	1.12	0.9919	33.51	0.62	2053.00	2782.81	0.443	0.34

Table 3. *Cont.*

DMU	Efficiency Score	i1	i2	i3	i4	o1	o2	o3	o4
Kansas	1.02255	0.69	1.0558	29.11	0.40	1767.00	3419.46	0.489	0.31
Kentucky	1	1.88	0.9963	41.10	0.48	1612.00	2522.23	0.492	0.40
Louisiana	1	0.54	0.8705	39.71	0.50	2307.00	3374.14	0.378	0.38
Massachusetts	1	8.57	1.4103	19.91	0.36	2610.00	4225.28	0.700	0.27
Maryland	1.00622	5.14	1.3954	21.68	0.20	1610.00	3448.70	0.610	0.31
Maine	1	0.71	1.3775	24.10	0.16	638.00	3779.09	0.661	0.23
Michigan	1.02937	1.31	1.1600	24.62	0.68	2099.00	3277.50	0.512	0.27
Minnesota	1	2.27	1.1547	16.05	0.72	1358.00	25,947.46	0.567	0.28
Missouri	1	0.02	0.9961	29.25	0.78	1611.00	2979.07	0.445	0.18
Mississippi	1	0.31	0.8937	28.26	0.60	2485.00	2554.42	0.359	0.30
Montana	1	0.78	1.0382	21.05	0.14	1555.00	4520.29	0.475	0.40
North Carolina	1	0.71	1.1117	22.88	1.00	1279.00	2540.43	0.450	0.23
North Dakota	1	7.14	0.9361	25.59	0.26	2005.00	6125.47	0.437	0.42
Nebraska	1	5.83	1.0791	29.05	0.18	1168.00	3829.86	0.514	0.37
New Hampshire	1.01757	1.32	1.3409	20.74	0.66	1008.00	3984.12	0.618	0.36
New Jersey	1	2.56	1.2890	34.05	0.56	2976.00	3848.45	0.644	0.60
New Mexico	1	0.89	1.1268	20.36	0.64	2067.00	2876.87	0.616	0.38
Nevada	1	0.31	0.9952	28.38	0.66	1840.00	3124.91	0.489	0.33
New York	1.05499	6.26	1.2284	27.51	0.94	2774.00	4278.89	0.596	0.39
Ohio	1.01952	1.28	1.0585	35.56	0.46	1735.00	3061.39	0.480	0.37
Oklahoma	1.02923	0.71	1.0137	24.59	0.34	1866.00	3644.81	0.446	0.35
Oregon	1	0.62	1.3349	19.28	0.58	655.00	3305.07	0.582	0.33
Pennsylvania	1.00539	1.70	1.2188	28.75	0.54	2168.00	3185.67	0.624	0.28
Rhode Island	1	2.14	1.4247	14.25	0.04	2575.00	4531.06	0.642	0.26
South Carolina	1	1.56	1.0255	22.53	0.42	1907.00	2346.02	0.438	0.33
South Dakota	1.08609	4.95	1.0824	26.34	0.32	2295.00	5348.51	0.503	0.44
Tennessee	1	2.52	0.9224	35.08	0.76	1838.00	2735.26	0.413	0.30
Texas	1.03728	0.59	1.0966	23.33	0.86	1811.00	3566.55	0.478	0.18
Vermont	1	0.73	1.0031	19.65	0.80	735.00	3117.00	0.481	0.40
Washington	1	2.00	1.2100	22.37	0.00	1335.00	3184.50	0.586	0.33
Wisconsin	1	2.32	1.4739	16.51	0.84	410.00	5277.58	0.735	0.27
Washington	1	0.92	1.2303	16.44	0.74	781.00	3369.97	0.607	0.28
Wisconsin	1	1.45	1.0489	27.62	0.30	1391.00	3251.07	0.534	0.46
West Virginia	1	0.82	1.0545	37.33	0.06	1605.00	2627.55	0.431	0.29
Wyoming	1	0.15	0.8911	24.02	0.22	1279.00	5343.58	0.390	0.60

According to Table 3, Alaska, Arkansans, Arizona, Connecticut, Hawaii, Idaho, Kentucky, Louisiana, Massachusetts, Maine, Minnesota, Missouri, Mississippi, Montana, North Carolina, North Dakota, Nebraska, New Jersey, New Mexico, Nevada, Oregon, Rhode Island, South Carolina, Tennessee, Utah, Virginia, Vermont, Washington, Wisconsin, West Virginia, and Wyoming have a score of 1, and they are relatively efficient.

Based on Ozcan (2009) and Ozcan (2014), a reference set, also known as best practices, was identified for each inefficient DMUs to become efficient [40,43].

Improvement options for the inefficient states are shown in Table 4.

Table 4. Improvement options for the inefficient states.

DMU	i1	i2	i3	i4	o1	o2	o3	o4
Alabama	0.00	0.00	–1.78	–0.24	–216.39	–238.75	0.04	0.16
California	–1.15	–0.03	0.00	–0.22	–456.29	–252.56	0.01	0.01
Colorado	0.00	0.00	0.00	0.00	–67.33	–212.93	0.01	0.03
Delaware	–0.44	–0.06	0.00	0.00	–39.28	–689.72	0.02	0.06
Florida	0.00	0.00	–2.16	–0.29	–7.37	–137.73	0.00	0.10
Georgia	0.00	–0.03	0.00	–0.35	–147.96	–1533.55	0.03	0.06
Iowa	0.00	–0.01	0.00	0.00	–27.35	–600.25	0.01	0.01
Illinois	–1.89	0.00	–4.02	–0.31	–45.31	–1429.02	0.03	0.02
Indiana	0.00	0.00	–1.81	–0.04	–159.90	–368.61	0.01	0.01
Kansas	0.00	0.00	–1.12	0.00	–27.28	–508.00	0.01	0.03
Maryland	–2.62	–0.16	0.00	0.00	–8.50	–139.93	0.00	0.02
Michigan	–0.09	–0.08	–3.18	–0.15	–111.96	–665.94	0.02	0.09
New Hampshire	–0.36	–0.05	–2.09	–0.17	–34.59	–385.83	0.01	0.01
New York	–4.89	–0.05	–4.90	–0.43	–641.48	–1191.63	0.03	0.02
Ohio	0.00	–0.01	0.00	0.00	–24.24	–446.69	0.01	0.01
Oklahoma	0.00	0.00	–0.08	0.00	–343.73	–651.85	0.01	0.01
Pennsylvania	–0.27	–0.05	–6.80	0.00	–39.73	–122.62	0.00	0.12
South Dakota	–3.60	0.00	0.00	0.00	–648.11	–1773.55	0.04	0.04

According to Table 4:

- The DMU that needs the most improvement in terms of “i1” is New York.
- The DMU that needs the most improvement in terms of “i2” is Maryland.
- The DMU that needs the most improvement in terms of “i3” is Pennsylvania.
- The DMU that needs the most improvement in terms of “i4” is New York.
- The DMU that needs the most improvement in terms of “o1” is South Dakota.
- The DMU that needs the most improvement in terms of “o2” is South Dakota.
- The DMUs that need the most improvement in terms of “o3” are South Dakota and Alabama.
- The DMU that needs the most improvement in terms of “o4” is Texas.

As shown in Table 5, independent samples *t*-tests were conducted to compare DMUs’ populations and gross domestic product (GDP) in the efficiency and inefficient conditions.

Table 5. Independent sample *t*-test results.

Dependent Variable	Efficiency Condition	N	Mean	Std. Deviation	P
Population	Efficiency	31	3,988,512.03	2,803,864.465	0.011
	Inefficiency	19	10,731,047.42	10,285,057.50	
GDP	Efficiency	31	252,090.90	199,971.078	0.018
	Inefficiency	19	735,539.84	802,756.118	

According to Table 5:

- There was a significant difference in the scores for efficiency (M = 3,988,512.03, SD = 2,803,864.465) and inefficiency (M = 10,731,047.42, SD = 10,285,057.50) conditions; t (48) = −2.795, p = 0.011 (in terms of population)
- There was a significant difference in the scores for efficiency (M = 252,090.90, SD = 19,9971.078) and inefficiency (M = 735,539.84, SD = 802,756.118) conditions; t (48) = –2.577, p = 0.018 (in terms of GDP)

5. Discussion

COVID-19 pandemic is a complex and unprecedented public health crisis worldwide. It is crucial to evaluate health systems for mitigating the impact of the COVID-19 pandemic [6].

Although all countries are affected by the pandemic, the United States is the country with the highest number of COVID-19 cases and deaths reported as of 27 June 2021. Therefore, both the CDC and each state's health department are committed to stopping its spread.

CDC's global COVID-19 response works toward the goals mentioned above by meeting the following objectives: strengthening healthcare system capacity to prevent, detect, and respond to local COVID-19 cases; mitigating COVID-19 transmission in the community, across borders, and in healthcare facilities; contributing to the scientific understanding of COVID-19; ensuring readiness to implement and evaluate vaccination programs [2].

Since healthcare systems rely heavily on scientific analysis to find results that can be generalized to a larger context [9], the evaluation should be both critical and as objective as possible [14]. Operation Strategy Matrix is a novel and objective evaluation tool. The matrix deal with how Strategic Decision Areas (Capacity, Supply Network, Process Technology, Development and Organization) affect Competitive Priorities (Quality, Cost, Delivery, Flexibility) [15].

DEA has been used widely in assessing healthcare efficiency in the United States and around the world at different levels of decision-making units [43]. Therefore, each U.S State's Operation Strategy Matrix was evaluated using DEA in the context of the COVID-19 pandemic. During the analysis, Strategic Decision Areas (Capacity, Supply Network, Process Technology, and Development and Organization) were considered as inputs while competitive priorities (Quality, Cost, Delivery, and Flexibility) were considered as outputs. Capacity was represented by "Contact Tracer Capacity Ratio". Supply Network was represented by "Distributed Vaccine Amount/Per Capita". Process Technology was represented by "Intensive Care Unit (ICU) Bed Capacity/Per 100,000 Population". Development and Organization was represented by "The COVID-19 Community Vulnerability Index (Theme 5: Healthcare System Factors)". Quality was represented by "Deaths/ 1M Population". The cost was represented by "Award Outlays/Per Capita Spending". Delivery was represented by "Vaccinated Rate (+1 Dose)". Flexibility was represented by "Available ICU Capacity (by percentage)". Additionally, since there are two undesirable (bad) outputs in the dataset, BCC (VRS)-Output Orientation Data Envelopment Analysis model was employed. Inputs (Capacity, Supply Network, Process Technology, and Development and Organization) are essential components of any operations including healthcare operations while outputs (Quality, Cost, Delivery, and Flexibility) are results of the inputs.

According to the results, 31 states are efficient, while 19 states are inefficient. Additionally, Connecticut, Louisiana, Minnesota, New Jersey, Rhode Island, Tennessee, Utah, Vermont, Washington, and Wyoming are fully efficient DMU based on efficiency scores and slack values.

A reference set was identified for each inefficient DMUs to become efficient. In the reference sets:

- New Mexico appeared eighteen times.
- Arizona appeared seven times.
- Oregon, Maine, and Idaho appeared six times.
- South Carolina appeared five times.
- Wyoming, West Virginia, Hawaii, and Arkansas appeared four times.

- Wisconsin, Massachusetts, and Connecticut appeared three times.
- Washington, Virginia, North Carolina, New Jersey, Missouri, and Kentucky appeared two times.
- Rhode Island, Nevada, and Mississippi appeared one time.

Additionally, the DMUs that need the most improvement are New York, Maryland, Pennsylvania, South Dakota, Alabama, and Texas.

It is relatively hard limiting the human-to-human transmission of COVID-19 in large communities because independent samples *t*-test results demonstrate that inefficient states have more population than efficient states. Moreover, 62.25% of the total US population lives in inefficient states, and 9 out of 12 states in the 3rd Population Quartile (7,845,049.50) are inefficient, while 9 out of 12 states in the 1st Population Quartile (1,790,876.50) are efficient. Furthermore, only 10.70% of the total US population lives in fully efficient states.

Economic and human mobility is maximum in the states with high GDP. For this reason, the spreading of the virus is fast. Hence, independent samples *t*-test results demonstrate that inefficient states have more GDP than efficient states. Moreover, 64.14% of the total US GDP is formed by inefficient states and 8 out of 12 states in the 3rd GDP Quartile (587,874.25) are inefficient, while 9 out of 12 states in the 1st GDP Quartile (91,862.25) are efficient. Additionally, only 13.69% of the total U.S GDP is formed by fully efficient states.

From the perspective of BEA region grouping [49]:

- 5 out of 6 states (83.3%) are efficient in the New England Region.
- 1 out of 5 states (20.0%) is efficient in the Mideast Region.
- 1 out of 5 states (20.0%) is efficient in the Great Lakes Region.
- 4 out of 7 states (57.1%) are efficient in the Plains Region.
- 9 out of 12 states (75.0%) are efficient in the Southeast Region.
- 2 out of 4 states (50.0%) are efficient in the Southwest Region.
- 4 out of 5 states (80.0%) are efficient in the Rock Mountain Region.
- 5 out of 6 states (83.3%) are efficient in the Far West Region.

New England and Far West are the most efficient regions while Mideast and Great Lakes are the least efficient regions by percentages. These results are in line with the population and GDP findings mentioned above. Additionally, three out of six states are fully efficient in the New England Region and 1 of 6 states is fully efficient in the Far West Region.

The SDGs are a universal agenda taking various aspects in development into account and applying them to all countries [75–77]. According to the United Nations Department of Economic and Social Affairs, SDG 3 is described as ensuring healthy lives and promoting well-being for all at all ages, and COVID-19 has shortened life expectancy [10]. United Nations has called the COVID-19 pandemic, beyond being a health emergency, as a systemic crisis that is already affecting economies and societies in unprecedented ways [72]. United Nations has created so that the countries cope with the pandemic, and the dashboards include some indicators such as the capacity of the healthcare system, vulnerability, and poverty [73]. These indicators are also included in our research model with the same or close names.

This study had some limitations. Since COVID-19 is a global pandemic, it is difficult to assess its effect on health systems. Additionally, data used for inputs and outputs were collected from many databases, public and private agencies, web pages, etc., in the US mentioned above. As such these databases were considered to be correct. Furthermore, data include 17 months from 22 January 2020 to 27 June 2021.

6. Managerial Implication and Conclusions

This study provides the first overview of the healthcare systems of U.S. states in the context of COVID-19, based on the first 17 months of the pandemic. The use of a novel evaluation tool named Operation Strategy Matrix constitutes the unique aspect of the study. Thus, the study is important for healthcare operations research literature.

The study results might contribute to both the federal and state health authorities; while the inefficient states can become efficient by applying our improvement suggestions, the federal government can develop new strategies to mitigate the COVID-19 pandemic considering our findings especially inductive statistical findings regarding population, GDP, and region.

Since SGDs address the global challenges we face, it could be yielded some critical projections for the future from the study's findings. Moreover, our research findings might help to ensure healthy lives in the context of COVID-19. The reference sets identified for each inefficient DMUs to become efficient can be used for both the US and other countries to achieve SDG Goal 3 amid COVID-19. Especially, fully efficient states (Connecticut, Louisiana, Minnesota, New Jersey, Rhode Island, Tennessee, Utah, Vermont, Washington, and Wyoming) can be served as a model to achieve Targets 3.8, 3. c, and 3.d.

Further studies can be developed new models applying different DEA approaches (Fuzzy DEA, Two-Stage DEA, Network DEA, etc.) to prioritize issues, challenges, drivers, and barriers related to healthcare systems and SDGs in the context of the COVID-19 pandemic.

Author Contributions: Conceptualization, A.Ö., H.K., M.Ş.G., and E.C.; methodology, A.Ö., H.K., M.Ş.G., and E.C.; software, A.Ö., H.K., M.Ş.G., and E.C.; validation, A.Ö., H.K., M.Ş.G., and E.C.; formal analysis, A.Ö., H.K., M.Ş.G., and E.C.; investigation, A.Ö., H.K., M.Ş.G., and E.C.; resources, A.Ö., H.K., M.Ş.G., and E.C.; data curation, A.Ö., H.K., M.Ş.G., and E.C.; writing—original draft preparation, A.Ö., H.K., M.Ş.G., and E.C.; writing—review and editing, A.Ö., H.K., M.Ş.G., and E.C.; visualization, A.Ö., H.K., M.Ş.G., and E.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Worldometer. Coronavirus Update. 2021. Available online: www.worldometers.info/coronavirus (accessed on 27 June 2021).
2. Centers for Disease Control and Prevention (CDC). CDC COVID-19 Global Response. 2020. Available online: www.cdc.govcoronavirus2019-ncovglobal-covid-19global-response.html (accessed on 21 November 2020).
3. Al-Taweel, D.; Al-Haqan, A.; Bajis, D.; Al-Bader, J.; Al-Taweel, A.R.M.; Al-Awadhi, A.; Al-Awadhi, F. Multidisciplinary academic perspectives during the COVID-19 pandemic. *Int. J. Health Plan. Manag.* **2020**, *35*, 1295–1301. [CrossRef]
4. Ogunkola, I.O.; Adebisi, Y.A.; Imo, U.F.; Odey, G.O.; Esu, E.; Lucero-Prisno, D.E. Rural communities in Africa should not be forgotten in responses to COVID-19. *Int. J. Health Plan. Manag.* **2020**, *35*, 1302–1305. [CrossRef]
5. Gökmen Kavak, D.; Öksüz, A.S.; Cengiz, C.; Kayral, İ.H.; Şenel, F.Ç. The importance of quality and accreditation in health care services in the process of struggle against Covid-19. *Turk. J. Med. Sci.* **2020**, *50*, 1760–1770. [CrossRef] [PubMed]
6. World Health Organization (WHO). Strengthening the Health System Response to COVID-19 Recommendations for the WHO European Region Policy Brief. 2020. Available online: https://apps.who.int/iris/bitstream/handle/10665/333072/WHO-EURO-2020-806-40541-54465-eng.pdf?sequence=1&isAllowed=y (accessed on 8 April 2020).
7. Aftab, W.; Siddiqui, F.J.; Tasic, H.; Perveen, S.; Siddiqi, S.; Bhutta, Z.A. Implementation of health and health-related sustainable development goals: Progress, challenges and opportunities-a systematic literature review. *BMJ Glob. Health* **2020**, *5*, e002273. [CrossRef]
8. Barcelona Instute for Global Health. The Sustainable Development Goals (SDGs) and Global Health. 2021. Available online: https://www.isglobal.org/en/-/global-health-inequities (accessed on 10 October 2021).
9. Block, D.J. *Healthcare Outcomes Management: Strategies for Planning*; Jones and Bartlett Publishers: Burlington, MA, USA, 2006.
10. United Nations Department of Economic and Social Affairs Sustainable Development. The 17 Goals. 2021. Available online: https://sdgs.un.org/goals (accessed on 29 August 2021).
11. Bappy, M.M.; Ali, S.M.; Kabir, G.; Paul, S.K. Supply chain sustainability assessment with Dempster-Shafer evidence theory: Implications in cleaner production. *J. Clean. Prod.* **2019**, *237*, 117771. [CrossRef]
12. Alam, S.T.; Ahmed, S.; Ali, S.M.; Sarker, S.; Kabir, G.; Ul-Islam, A. Challenges to COVID-19 vaccine supply chain: Implications for sustainable development goals. *Int. J. Prod. Econ.* **2021**, *239*, 108193. [CrossRef]
13. Donabedian, A. Evaluating the Quality of Medical Care. *Milbank Q.* **2005**, *83*, 691–729. [CrossRef] [PubMed]

14. Jenkinson, C. *Assessment and Evaluation of Health and Medical Care: A Methods Text*; Open University Press: Buckingam, PA, USA, 1977.
15. Slack, N.; Lewis, M. *Operations Strategy*, 5th ed.; Pearson Education Limited: Harlow, UK, 2017.
16. O'Leary, N.; Kingston, L.; Griffin, A.; Morrissey, A.-M.; Noonan, M.; Kelly, D.; Doody, O.; Niranjan, V.; Gallagher, A.; O'Riordan, C.; et al. COVID-19 healthcare policies in Ireland: A rapid review of the initial pandemic response. *Scand. J. Public Health* **2021**, *49*, 713–720. [CrossRef]
17. Tsai, Y.; Yang, T. COVID-19 Outbreak and Voluntary Demand for Non-COVID-19 Healthcare: Evidence from Taiwan. *SSRN Electron. J.* **2020**. [CrossRef]
18. Adwibowo, A. COVID 19 healthcare facility demand forecasts for rural residents. *medRxiv* **2020**. [CrossRef]
19. Alshammari, N.; Sarker, M.N.I.; Kamruzzaman, M.M.; Alruwaili, M.; Alanazi, S.A.; Raihan, M.L.; AlQahtani, S.A. Technology-driven 5G enabled e-healthcare system during COVID-19 pandemic. *IET Commun.* **2021**, 1–15.
20. Brodie, R.J.; Ranjan, K.R.; Verreynne, M.-L.; Jiang, Y.; Previte, J. Coronavirus crisis and health care: Learning from a service ecosystem perspective. *J. Serv. Theory Pract.* **2021**, *31*, 225–246. [CrossRef]
21. Arlotti, M.; Ranci, C. The Impact of COVID-19 on Nursing Homes in Italy: The Case of Lombardy. *J. Aging Soc. Policy* **2021**, *33*, 431–443. [CrossRef]
22. Rodríguez, Y.; Hignett, S. Integration of human factors/ergonomics in healthcare systems: A giant leap in safety as a key strategy during Covid-19. *Hum. Factors Ergon. Manuf.* **2021**, *31*, 570–576. [CrossRef] [PubMed]
23. Akiyama, M.J.; Arnsten, J.H.; Roth, S. New normal: Caring for hospitalised patients in the Bronx, New York, during COVID-19. *Intern. Med. J.* **2021**, *51*, 288–290. [CrossRef] [PubMed]
24. Tasri, Y.D.; Tasri, E.S. Improving clinical records: Their role in decision-making and healthcare management–COVID-19 perspectives. *Int. J. Health Manag.* **2020**, *13*, 325–336.
25. Bel, G.; Gasulla, Ó.; Mazaira-Font, F.A. The Effect of Health and Economic Costs on Governments' Policy Responses to COVID-19 Crisis under Incomplete Information. *Public Adm. Rev.* **2021**, 1–16. [CrossRef]
26. Chamboredon, F.; Roman, C.; Colson, S. COVID-19 pandemic in France: Health emergency experiences from the field. *Int. Nurs. Rev.* **2020**, *67*, 326–333. [CrossRef] [PubMed]
27. Leite, H.; Lindsay, C.; Kumar, M. COVID-19 Outbreak: Implications on Healthcare Operations. *TQM J.* **2021**, *33*, 247–256. [CrossRef]
28. United Nations. Goal 3: Ensure Healthy Lives and Promote Well-Being for All at All Ages. 2021. Available online: https://www.un.org/sustainabledevelopment/health/ (accessed on 18 October 2021).
29. World Health Organization (WHO). Sustainable Development Goals (SDGs). 2021. Available online: https://www.who.int/health-topics/sustainable-development-goals#tab=tab_1 (accessed on 18 October 2021).
30. Rajan, S.; Ricciardi, W.; McKee, M.; McKee, M. The SDGs and health systems: The last step on the long and unfinished journey to universal health care? *Eur. J. Public Health* **2020**, *30*, i28–i30. [CrossRef]
31. Kruk, M.E.; Gage, A.D.; Arsenault, C.; Jordan, K.; Leslie, H.H.; Roder-DeWan, S.; Adeyi, O.; Barker, P.; Daelmans, B.; Doubova, S.V.; et al. High-quality health systems in the Sustainable Development Goals era: Time for a revolution. *Lancet Glob. Health.* **2018**, *6*, e1196–e1252. [CrossRef]
32. Gavurova B, Kocisova K, Sopko, J. Health system efficiency in OECD countries: Dynamic network DEA approach. *Health Econ. Rev.* **2021**, *11*, 1–25.
33. Jordi, E.; Pley, C.; Jowett, M.; Abou Jaoude, G.J.; Haghparast-Bidgoli, H. Assessing the efficiency of countries in making progress towards universal health coverage: A data envelopment analysis of 172 countries. *BMJ Glob. Health* **2020**, *5*, e002992. [CrossRef] [PubMed]
34. Ramanathan, R. *An Introduction to Data Envelopment Analysis a Tool for Performance Measurement*; Sage Publications India Pvt Ltd.: New Delhi, India, 2003.
35. Ray, S.C. *Data Envelopment Analysis Theory and Techniques for Economic and Operations Research*; Cambridge University Press: New York, NY, USA, 2004.
36. Tone, K. Radial DEA Models. In *Advances in DEA Theory and Applications with Extensions to Forecasting Models*; Tone, K., Ed.; John Wiley & Sons Ltd.: Hoboken, NJ, USA, 2017.
37. Charnes, A.; Cooper, W.W.; Lwein, A.Y.; Seiford, L.M. *Data Envelopment Analysis: Theory, Methodology, and Application*; Springer: New York, NY, USA, 1994.
38. Emrouznejad, A.; Cabanda, E. Managing Service Productivity Using Data Envelopment Analysis. In *Managing Service Productivity Using Frontier Efficiency Methodologies and Multicriteria Decision Making for Improving Service Performance*; Emrouznejad, A., Cabanda, E., Eds.; Springer: Berlin/Heidelberg, Germany, 2014.
39. Gok, M.S.; Sezen, B. Analyzing the Efficiencies of Hospitals: An Application of Data Envelopment Analysis. *J. Glob. Strat. Manag.* **2011**, *2*, 137. [CrossRef]
40. Ozcan, Y.A. *Quantitative Methods in Health Care Management: Techniques and Applications*, 2nd ed.; John Wiley & Sons, Inc.: San Francisco, CA, USA, 2009.
41. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
42. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]

43. Ozcan, Y.A. *Health Care Benchmarking and Performance Evaluation an Assessment Using Data Envelopment Analysis (DEA)*; Springer: New York, NY, USA, 2014.
44. Emrouznejad, A.; Tavana, M.; Hatami-Marbini, A. The State of the Art in Fuzzy Data Envelopment Analysis. In *Performance Measurement with Fuzzy Data Envelopment Analysis*; Emrouznejad, A., Tavana, M., Eds.; Springer: Berlin/Heidelberg, Germany, 2014.
45. Cooper, W.W.; Seiford, L.M.; Tone, K. *Introduction to Data Envelopment Analysis and Its Uses with DEA-Solver and References*; Springer: New York, NY, USA, 2006.
46. Hua, Z.; Bian, Y. DEA with Undesirable Factors. In *Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis*; Zhu, J., Cook, W.D., Eds.; Springer: New York, NY, USA, 2007.
47. Golany, B.; Roll, Y. An application procedure of DEA. *Omega* **1989**, *17*, 237–250. [CrossRef]
48. CovidActNow. Covid Act Now API (v2.0.0-Beta.1). 2021. Available online: https://apidocs.covidactnow.org/ (accessed on 27 June 2021).
49. Bureau of Economic Analysis (BEA). Gross Domestic Product 1st Quarter 2021. 2021. Available online: https://www.bea.gov/sites/default/files/2021-06/qgdpstate0621.pdf (accessed on 18 October 2021).
50. Seiford, L.M.; Zhu, J. Modeling undesirable factors in efficiency evaluation. *Eur. J. Oper. Res.* **2002**, *142*, 16–20. [CrossRef]
51. Karuppan, C.M.; Dunlap, N.E.; Waldrum, M.R. *Operations Management in Healthcare Strategy and Practice*; Springer: New York, NY, USA, 2016.
52. McLaughlin, D.B.; Hays, J.M. *Healthcare Operations Management*; Health Administration Press: Chicago, IL, USA; AUPHA Press: Washington, DC, USA, 2008.
53. Bergeron, B.P. *Performance Management in Healthcare: From Key Performance Indicators to Balanced Scorecard*, 2nd ed.; CRC Press: Boca Raton, FL, USA; Taylor & Francis Group: Milton Park, UK, 2018.
54. CDC. Contact Tracing. 2020. Available online: https://www.cdc.gov/coronavirus/2019-ncov/daily-life-coping/contact-tracing.html (accessed on 18 November 2020).
55. Slack, N.; Chambers, S.; Johnston, R. *Operations Management*, 5th ed.; Pearson Education Limited: Essex, UK, 2007.
56. Sakib, N.; Ibne Hossain, N.U.; Nur, F.; Talluri, S.; Jaradat, R.; Lawrence, J.M. An assessment of probabilistic disaster in the oil and gas supply chain leveraging Bayesian belief network. *Int. J. Prod. Econ.* **2021**, *235*, 108107. [CrossRef]
57. El Amrani, S.; Ibne Hossain, N.U.; Karam, S.; Jaradat, R.; Nur, F.; Hamilton, M.A.; Ma, J. Modelling and assessing sustainability of a supply chain network leveraging multi Echelon Bayesian Network. *J. Clean. Prod.* **2021**, *15*, 302.
58. Shahed, K.S.; Azeem, A.; Ali, S.M.; Moktadir, M.A. A supply chain disruption risk mitigation model to manage COVID-19 pandemic risk. *Environ. Sci. Pollut. Res.* **2021**, 1–16.
59. CDC. Key Things to Know About COVID-19 Vaccines. 2021. Available online: https://www.cdc.gov/coronavirus/2019-ncov/vaccines/keythingstoknow.html (accessed on 30 June 2021).
60. CDC. COVID-19 Vaccination Program Interim Operational Guidance Jurisdiction Operations. 2020. Available online: https://www.cdc.gov/vaccines/imz-managers/downloads/COVID-19-Vaccination-Program-Interim_Playbook.pdf (accessed on 30 June 2021).
61. Boucetta, M.; Hossain, N.U.I.; Jaradat, R.; Keating, C.; Tazzit, S.; Nagahi, M. The architecture design of electrical vehicle infrastructure using viable system model approach. *Systems* **2021**, *9*, 19. [CrossRef]
62. Centers for Disease Control and Prevention (CDC). About COVID-19 Vaccine Delivered and Administration Data. 2021. Available online: https://www.cdc.gov/coronavirus/2019-ncov/vaccines/distributing/about-vaccine-data.html (accessed on 30 June 2021).
63. Pan American Health Organization (PAHO). Health Technology Management. 2020. Available online: https://www.paho.org/hq/index.php?option=com_content&view=article&id=11582:health-technology-management&Itemid=41686&lang=en (accessed on 12 November 2020).
64. CovidActNow. Introduction and Contents (Update 26 May 2020). USA. 2020. Available online: https://covidactnow.org/ (accessed on 30 June 2021).
65. Surgo Ventures. Vulnerable Communities and COVID-19: The Damage Done, and the Way Forward. 2021. Available online: https://surgoventures.org/resource-library/report-vulnerable-communities-and-covid-19 (accessed on 30 June 2021).
66. Maru, H.; Haileslassie, A.; Zeleke, T.; Esayas, B.; Rescia, A.; Gmada, S.S. Analysis of Smallholders' Livelihood Vulnerability to Drought across Agroecology and Farm Typology in the Upper Awash Sub-Basin, Ethiopia. *Sustainability* **2021**, *13*, 9764. [CrossRef]
67. CovidActNow. Risk Levels & Key Metrics. 2021. Available online: https://covidactnow.org/covid-risk-levels-metrics#vulnerability (accessed on 30 June 2021).
68. Surgo Ventures. Precision for COVID. 2021. Available online: https://precisionforcovid.org/ccvi (accessed on 27 June 2021).
69. Reid, R.D.; Sanders, N.R. *Operations Management an Integrated Approach*, 5th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2013.
70. USASpending.Gov. COVID-19 Spending. 2021. Available online: https://www.usaspending.gov/disaster/covid-19?publicLaw=all (accessed on 27 June 2021).
71. Buchbinder, S.B.; Shanks, N.H. *Introduction to Health Care Management*, 3th ed.; Jones & Bartlett Learning: Burlington, MA, USA, 2017.
72. Mamun, A.A.; Khaled, A.A.; Ali, S.M.; Chowdhury, M.M. A heuristic approach for balancing mixed-model assembly line of type i using genetic algorithm. *Int. J. Prod. Res.* **2012**, *50*, 5106–5116. [CrossRef]
73. Duan, J.; Li, H.; Zhang, Q. Multiobjective optimization of buffer capacity allocation in multiproduct unreliable production lines using improved adaptive NSGA-II algorithm. *Kuwait J. Sci.* **2020**, *48*, 37–49. [CrossRef]
74. Coll-Serrano, V.; Benítez, R.; Bolós, V. *Data Envelopment Analysis with deaR, R Package Version 1.2.0*; R Core Team: Vienna, Austria, 2018.

75. Tasaki, T.; Tajima, R.; Kameyama, Y.; Randall, A. Measurement of the Importance of 11 Sustainable Development Criteria: How Do the Important Criteria Differ among Four Asian Countries and Shift as the Economy Develops? *Sustainability* **2021**, *13*, 9719. [CrossRef]
76. United Nations Development Programme (UNDP). *2020 Human Development Perspectives COVID-19 and Human Development: Assessing the Crisis, Envisioning the Recovery*; UNDP: New York, NY, USA, 2020. Available online: http://hdr.undp.org/sites/default/files/covid-19_and_human_development_0.pdf (accessed on 29 August 2021).
77. United Nations Development Programme. COVID-19: New UNDP Data Dashboards Reveal Huge Disparities among Countries in Ability to Cope and Recover. 2020. Available online: https://www.undp.org/press-releases/covid-19-new-undp-data-dashboards-reveal-huge-disparities-among-countries-ability (accessed on 29 August 2021).