Efficiency Evaluation of COVID-19 Prevention and Control Based on DEA Model

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***Abstract*—The COVID-19 outbreak has presented a significant challenge to the medical reserve resources and management policies of nations. This study employs the DEA model to evaluate the efficiency of epidemic prevention and control in select countries. The results showed that a higher investment in epidemic prevention and control does not necessarily lead to better outcomes, as there is little correlation between the efficiency of prevention and control and the amount of resources invested. Stricter regulation may impose social and economic costs, implying that more stringent measures are not always optimal. Among the sample countries for efficiency measurement, Japan with a small population had relatively effective efficiency, while India with a relatively young aging population had the highest efficiency improvement. The above conclusions have good reference significance for countries to prevent the next pandemic.**

***Index Terms*—DEA; COVID-19; Prevention and control efficiency; Redundancy analysis**

I. Introduction

CORONA virus disease 2019, also known as COVID-19, its outbreak has impacted over 200 countries and regions, with unprecedented symptom development, transmission speed, and epidemic scope. Governments have implemented various measures to combat the pandemic, including border closures, production and school suspensions, and urging citizens to stay at home in order to control its spread. Therefore, enhancing the prevention and control efficiency is crucial for curbing the spread of the epidemic and safeguarding people's fundamental life security. Since the outbreak of COVID-19, numerous scholars and experts have paid great attention to studying its transmission characteristics, treatment, impact as well as prevention and control efficiency (Yang 2022, Youssef 2022, Shi 2022, Hejazi 2023, Chellafe 2023, and Mattera 2022).

As for the research on the prevention and control efficiency and policy management of COVID-19. All countries have weaknesses in their preparedness to handle a pandemic crisis. No country has achieved high levels of preparedness to effectively cope with a major epidemic or pandemic (Coccia 2022). Among the lessons learned for dealing with the impact of the next pandemic, the design of effective health policies for prevention and preparedness of future pandemics should be underpinned in a good governance of countries and adoption of new technology, rather than strict and generalized health polices having ambiguous effects of containment in society (Coccia 2023). By investigating the efficiency of COVID-19 prevention and control at the city level in China, and discussing the impact of doctor resources on prevention and control efficiency, there is obvious regional heterogeneity in the implementation of urban epidemic prevention and control measures. (Shen et al 2021). MRC Global Center for Infectious Diseases of Imperial College London predicts epidemic intervention measures through modeling and concludes that if relevant epidemic prevention and control measures were not changed, a large number of people would die (Ferguson et al 2020). Therefore, the British government changed its epidemic prevention and control strategy. Through the use of the data on confirmed cases and deaths in Spain and Italy before and after their respective countries' lockdowns, and find that the incidence trend significantly reduces in both countries after adopting isolation and social distancing measures (Tobias 2020, and Saez et al 2020).

Data envelopment analysis (short for DEA) is a useful tool for evaluating efficiency. By utilizing DEA and machine-learning methods to evaluate countries' performance during the epidemic, it has been found that Bangladesh, Chile, Japan and other countries were more efficient (Taherinezhad et al 2022). There is a study using DEA method and find that the better the anti-pandemic by a given country is, the lower the number of hospitalized patients and reproduction rate is (Stepank et al 2021). Similarly, one research uses the DEA model and simulation of the general sequential structure network to evaluate the efficiency of each country (Pereira et al 2022). The same method is used in a study to evaluate the effectiveness of COVID-19 prevention and control, the results indicate that China's medical resource allocation is DEA effective, resulting in a good epidemic prevention and control outcome. European countries exhibit generally low levels of medical resource allocation efficiency, while Japan and South Korea demonstrate relatively high levels of such efficiency. Russia has the highest redundancy (Wu et al 2020).

The main purpose of this study is to measure the prevention and control efficiency of COVID-19 in select countries and analyze the lessons learned from national interventions such as vaccination, nucleic acid testing and containment to prevent the next pandemic. It is worth considering whether higher vaccination rates, stricter containment protocols, and heightened epidemic prevention and control efficiency are interrelated.

Referring to previous studies, this study selected three input indicators in the DEA model: the number of nucleic acid tests per thousand people, the dose of vaccination per thousand people and the strict index, and three output indicators: the number of confirmed cases per thousand people, the national happiness index and the cost per capita.

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The comprehensive efficiency, pure technical efficiency and scale efficiency of national epidemic prevention and control were analyzed. Secondly, the DEA model was used to assess the redundancy of each country's input to comprehensively evaluate the risks posed by COVID-19. In the review of research papers on the efficiency measurement of COVID-19 prevention and control, the number of nucleic acid tests and the strict index have not been used as input indicators. In addition, this study selected the national happiness index published by the United Nations report as an output indicator to assess the impact of COVID-19 on the happiness of a country's residents. Under the epidemic situation, people's livelihood and production are most affected, so it is reasonable and feasible to use the happiness index as an output indicator.

The structure of this paper is as follows: In Section 2, the concept of CCR model, BCC model and the projection model are introduced. In Section 3, the design of input and output indicators for measuring prevention and control efficiency of COVID-19 are given. In Section 4, data collection and processing methods are explained. In Section 5, the results of comprehensive efficiency, pure technical efficiency, scale efficiency and investment redundancy are analyzed. The conclusion and suggestions are presented in Section 6.

II. DEA Model

In this work, DEA model was used to measure the efficiency of COVID-19 prevention and control. In the following, the traditional model CCR of DEA was first introduced. By adding constraint conditions $\sum_{j=1}^{n}\lambda_j = 1$ to the CCR model, the BCC model can be obtained. These two models can be used to calculate the comprehensive efficiency, pure technical efficiency and scale efficiency of prevention and control effectiveness measurement across 14 countries. Finally, the DEA projection model was used to analyze the redundancy of investment in epidemic prevention and control of various countries, which was used to measure the resources that failed to play an effective role in COVID-19 prevention and control.

A. CCR model

The CCR model is the first model established in the history of DEA model. It calculates the efficiency of resource allocation under the condition of constant return to scale. There are *n* decision-making units DMU_j, $j = 1,2\cdots,n$, each DMU_j has *m* types of inputs and *s* types of outputs, the input vector is $X_j = (x_{1j}, x_{2j}\cdots,x_{mj})^T$, and the output vector is $Y_j = (y_{1j}, y_{2j}\cdots,y_{sj})^T$, where x_{ij} is the quantity of the *i*th input index of DMU_j, y_{rj} is the quantity of the *r*th output index of DMU_j. The following model can be obtained

$$\max \frac{u^{\mathrm{T}}y_0}{v^{\mathrm{T}}x_0}$$

$$s.t\begin{cases}\dfrac{u^{\mathrm{T}}y_j}{v^{\mathrm{T}}x_j} \le 1, j = 1,2,\cdots,n,\\ u \ge 0, v \ge 0, u \ne 0, v \ne 0,\end{cases}$$

where $v = (v_1, v_2,\cdots,v_m)^T$ and $u = (u_1, u_2,\cdots,u_s)^T$ represent the weight coefficient of the *m*th input and the *s*th output, respectively. Let $t = \frac{1}{v^{\mathrm{T}}x_0} > 0, \omega = tv, \mu = tu$, after Charness-Cooper transformation, it can be changed into the following linear programming model

$$\min \theta$$

$$s.t\begin{cases}\sum_{j=1}^{n} x_j\lambda_j \le \theta x_0,\\ \sum_{j=1}^{n} y_j\lambda_j \le y_0,\\ \lambda_j \ge 0, j = 1,2,\cdots,n,\end{cases}$$

where x_0, y_0 is the input and output vector of the selected DMU_0, λ is the combination proportion of *n* DMUs in the reconstructed effective DMU combination, θ is the efficiency value of DMU_0.

In the dual programming of the above programming, relaxation variable s^- and residual variable s^+ are introduced to convert inequality constraints into equality constraints, and the model is simplified as follows

$$\min \theta$$

$$s.t.\begin{cases}\sum_{j=1}^{n} \lambda_j x_j + s^- = \theta x_0,\\ \sum_{j=1}^{n} \lambda_j y_j - s^+ = y_0,\\ \lambda_j \ge 0, j = 1,2,\cdots,n,\\ s^+ \ge 0, s^- \ge 0.\end{cases}$$

If $\theta^* = 1$ and $s^{*+} = s^{*-} = 0$ then the DMU is DEA effective, and it is both technically effective and scale effective. If $\theta^* = 1$, and at least one input or output is greater than 0, then the DMU is weak DEA effective, and it is not both technically effective and scale effective. If $\theta^* < 1$, the DMU is non-DEA efficient, and it is neither technically efficient nor scale efficient.

B. BCC model

The BCC model expands the DEA analysis of fixed returns to scale by incorporation variable returns to scale. Therefore, by improving the constraint conditions of CCR model and adding assumption $\sum_{j=1}^{n}\lambda_j = 1$, we can get

$$\min \theta$$

$$s.t.\begin{cases}\sum_{j=1}^{n} \lambda_j x_j + s^- = \theta x_0,\\ \sum_{j=1}^{n} \lambda_j y_j - s^+ = y_0,\\ \sum_{j=1}^{n} \lambda_j = 1,\\ s^+ \ge 0, s^- \ge 0.\end{cases}$$

Through the above two models, the comprehensive efficiency, technical efficiency, pure technical efficiency and scale efficiency of each DMU can be calculated. Among them, comprehensive efficiency refers to the ratio of minimum cost to actual cost while maintaining output. Technical efficiency refers to the ratio of actual output to ideal output while keeping *DMU* input constant. Pure technical efficiency measures the gap between a *DMU*'s current production level and state-of-the-art technology. Scale efficiency refers to the difference between the production frontier when the return to scale is variable and the return to scale is constant.

C. DEA Projection

In analysis, for non-DEA effective *DMU*, we cannot help thinking about how to transform non-DEA effective into DEA effective. At this time, the projection method will be applied, and the dual problem model is as follows

$$\min\ [\theta - \varepsilon(\hat{e}^T s^- + e^T s^+)]$$

$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j y_j + s^- = \theta x_0, \\ \sum_{j=1}^{n} \lambda_j y_j - s^+ = y_0, \\ \lambda_j \geq 0, j = 1,2,\cdots,n, \\ \quad s^+ \geq 0, s^- \geq 0. \end{cases}$$

Let the optimal solution of linear programming be λ, s^+, s^-, θ and let $(\hat{x}_0, \hat{y}_0)$ with $\begin{cases} \hat{x}_0 = \theta x_0 - s^- \\ \hat{y}_0 = y_0 + s^+ \end{cases}$ be the projection of non-effective decision unit to effective unit. Wherein, input redundancy is $\Delta x_0 = x_0 - \hat{x}_0 = (1 - \theta)x_0 + s^-$, output deficit is $\Delta y_0 = y_0 - \hat{y}_0 = s^+$.

III. Index Design of Epidemic Prevention and Control Efficiency

Effective measures are an essential part of epidemic control, and countries leverage of their comprehensive national strength and medical resources to prevent epidemics. Therefore, the response measures taken by countries in response to COVID-19 serve as input indicators, while the outcomes achieved in prevention and control serve as output indicators. To avoid inaccuracies in the results caused by varying stages of epidemic progression, the time period is divided into two phases: the first phase encompasses the more severe outbreak from 2020 to 2021, while the second phase pertains to effective epidemic control measures implemented between 2021 and 2022.

A. Input index design

On the basis of inclusiveness, the COVID-19 prevention and control measures implemented by various countries should be fully considered in two aspects: a country's prevention and control measures should encompass its testing intensity to differentiate between the infected and the vulnerable, as well as its response intensity to the epidemic. Therefore, two indicators, the number of nucleic acid tests per thousand people and the strict index, have been selected to reflect the prevention and control measures. The strict index (Our world in data, 2022) is a composite index calculated based on 13 subdivisions. Second, the number of doses per thousand was chosen to measure the prevalence of COVID-19 vaccination in each country. As shown in Table I.

B. Output index design

For the purpose of designing output indicators to measure epidemic prevention and control efficiency, the number of confirmed cases per 1000 people was selected as one of the output indicators. The daily count of confirmed cases provides a visual representation of the magnitude of an outbreak within a given country. Secondly, the national happiness index was selected as another output indicator. The happiness index is a valuable indicator of how a country's well-being has changed during a pandemic. According to the World Happiness Report (World Happiness Report, 2020), worry and stress after the COVID-19 pandemic increased by eight percent in 2020 and four percent in 2021. Life satisfaction among young people has fallen. Second, in countries with high levels of trust in public institutions and low levels of inequality, the number of deaths due to COVID-19 between 2020 and 2021 is significantly lower. Finally, the per capita cost index was chosen to reflect the decline in per capita GDP caused by economic stagnation and production shutdowns under the pandemic. This work argues that it is reasonable and feasible to select confirmed cases per 1000 people, cost per capita, and national happiness index as output indicators. As shown in Table I.

TABLE I
INDEX DESCRIPTION

	index	type
Input index	Nucleic acid tests per thousand people	+
	Vaccination dose per thousand people	+
	Strict index	+
Output index	Confirmed cases per thousand people	-
	Cost per capita	-
	National happiness index	+

Note: *+ means positive; - means negative*

C. Data collection

Considering national measures for epidemic prevention and control, as well as data availability, this study has selected fourteen countries as samples. For nucleic acid detection, vaccination rates, strictness index, and confirmed cases were obtained from "Our World in Data." (Our world in data, 2022, https://ourworldindata.org). The data, supported by an Oxford University laboratory, has a degree of authenticity and rigor. Second, the national happiness index from the world happiness report issued by the United Nations (World happiness report, 2020 2021, https: //worldhappiness. report/ ed), which is based on the Gallup world poll, has a certain authenticity and reliability. The nations of the world GDP data from Economy Prediction System.

D. Data cleaning

In order to reduce the impact of population differences on the accuracy of data, relative indicators such as the number of nucleic acid tests per thousand people were used for calculation. Since the rigidly indexed data obtained is daily data, the data are disambiguated and averaged.

For the per capita cost index, it is assumed that the international economic environment will remain stable and there will be no occurrence of epidemics or other economic crises.Through the statistics of the GDP data of 14 countries from 2016 to 2021, calculate the average growth rate of GDP from 2016 to 2019, then predict the theoretical GDP value in 2020 and 2021, compare with the actual value to get the GDP difference, get the decrease or increase of per capita GDP. The formula is as follows

$$\frac{1}{3}\sum_{i=2016}^{2018}\frac{x_{i+1}-x_i}{x_i}=\theta,$$

$$(1+\theta)x_{2019}=\hat{x}_{2020},$$

where θ is the average GDP growth rate, x_i is the actual value of GDP in the ith year.

Since the input-output indicators of DEA model are generally positive indicators, the number of confirmed cases per thousand and the per capita cost in this paper are actually reverse indicators, even some of the per capita cost has a value less than 0, these two indicators are normalized and mapped to the interval [0,1], and then the following calculation is performed, as shown in the following formula.

$$x_{ij}^{'}=\frac{\max_i(x_{ij})-x_{ij}}{\max_i(x_{ij})-\min_i(x_{ij})},$$

where x_{ij} represents the value of the jth index of the ith sample.

IV. Result Analysis

A. Comprehensive efficiency analysis

Based on the above construction of the input-output indicator system, the model was solved by using Stata software to obtain the comprehensive efficiency of the epidemic prevention and control in 14 countries, as shown in Figure I.

FIGURE I
COMPREHENSIVE EFFICIENCY OF EPIDEMIC PREVENTION AND CONTROL IN 14 COUNTRIES

Country	2020	2021
Australia	0.692	1
Canada	0.695	0.961
France	0.67	0.867
Germany	0.745	0.84
India	0.568	1
Italy	0.535	0.735
Japan	1	1
Mexico	0.928	1
Russia	0.592	1
South Korea	0.656	1
Thailand	1	0.851
Turkey	0.667	1
UK	0.663	1
USA	0.677	0.971

Figure I reveals that only Japan's comprehensive efficiency was DEA effective during 2020 and 2021. This could be attributed to the country's small population, which facilitated swift and efficient deployment of health resources by the government in response to emergencies. Thailand was effective in 2020 but not in 2021, and its comprehensive efficiency stood in contrast to that of other countries. Among the 14 countries, Thailand was the only one where comprehensive efficiency declined. It was a tourist country. Despite the challenging circumstances posed by the pandemic, the Thai government made a calculated decision to prioritize economic stability and continued development of the tourism industry, opting not to impose strict restrictions on movement which unfortunately resulted in further spread of COVID-19.

In 2021, seven countries changed their comprehensive efficiency from non-DEA effective to DEA effective: Australia, India, Mexico, Russia, South Korea, Turkey, and the United Kingdom. Among them, India experienced the most significant improvement with a growth rate of 76.06%, surpassing all other countries in terms of efficiency enhancement. Due to difference in population structure, India's aging level is lower than that of European countries. The young population in India has developed antibodies against the virus, resulting in a herd immunity effect and providing basic conditions for entering the "stable phase" of COVID-19. However, there were still five countries whose efficiency was always non-DEA effective, namely, Canada, France, Germany, Italy and the United States. Among them, Italy exhibited the lowest average efficiency at 0.635, which can be attributed to its unique governmental policies and perspectives on epidemic control. As the epicenter of Europe's outbreak, Italy lifted its lockdown and travel restrictions in June 2020, resulting in a resurgence of COVID-19 cases during the latter half of that year. Meanwhile, the United States experienced a modest improvement with a comprehensive efficiency increase of 43.43%.

Overall, in 2020, 92.86% of countries were non-DEA effective. In 2021, 42.86% of countries were non-DEA effective. This indicates that the prevention and control of COVID-19 in the world has been gradually strengthened. However, further improvements in efficiency are still necessary.

B. Pure technical efficiency and scale efficiency analysis

Through the model, we can get the pure technical efficiency and scale efficiency of fourteen countries in the past two years, as shown in Table II.

TABLE II
PURE TECHNICAL EFFICIENCY AND SCALE EFFICIENCY OF FOURTEEN COUNTRIES

Country	2020			2021		
	PTE	SCALE	RTS	PTE	SCALE	RTS
Australia	1.000	0.692	drs	1.000	1.000	—
Canada	0.938	0.741	drs	1.000	0.961	drs
France	0.883	0.760	drs	0.878	0.987	drs
Germany	1.000	0.745	drs	0.988	0.850	drs
India	1.000	0.568	drs	1.000	1.000	—
Italy	0.640	0.836	drs	0.739	0.995	drs
Japan	1.000	1.000	—	1.000	1.000	—
Mexico	1.000	0.928	drs	1.000	1.000	—
Russia	0.642	0.922	irs	1.000	1.000	—
Korea	0.733	0.895	drs	1.000	1.000	—
Thailand	1.000	1.000	—	0.877	0.970	irs
Turkey	1.000	0.667	drs	1.000	1.000	—
UK	1.000	0.663	drs	1.000	1.000	—
USA	0.875	0.774	drs	1.000	0.971	drs

Note: *drs means diminishing returns to scale; irs means increasing returns to scale; — means constant return on scale.*

According to Table II, Japan was the only country that demonstrated DEA effective in both pure technical efficiency and scale efficiency over the past two years. Russia and South Korea have transitioned from being non-DEA effective to

DEA effective, indicating that both countries have improved in terms of pure technology and the scale of prevention and control, leading them towards a relatively optimal situation.

Australia, India, Mexico, Turkey, and the United Kingdom changed from diminishing return to scale to constant return to scale. And the pure technical efficiency of these five countries was effective in two years. Their scale efficiency was ineffective in 2020 but effective in 2021, indicating that the key to restricting their epidemic prevention and control efficiency lies in scale rather than technology level. Canada, France, Germany, Italy and the United States showed diminishing return to scale in two years, indicating that these five countries had excessive investment in epidemic prevention and control with relatively low resource utilization efficiency and a mismatch between resource investment and prevention and control effectiveness. In 2021, Canada and the United States achieved effective pure technical efficiency while their scale efficiency remained ineffective despite some improvement. The two countries can improve the return to scale by expanding the scale of epidemic prevention and control. Thailand achieved DEA effective in 2020, increased returns to scale in 2021, and decreased both pure technical efficiency and scale efficiency. This indicated that the country's relaxation of epidemic control measures was consistent with its economic development policies.

C. Input redundancy analysis

Finally, this study conducts projection analysis on countries with non-DEA effective. In terms of model setup, the input-oriented model is adopted in order to minimize inputs while maintaining at least the current output level. This approach aligns with the overall context of COVID-19 prevention and control, where improving inputs can effectively enhance epidemic prevention and control efficiency. Stata software was used to calculate the input redundancy values for each country in both 2020 and 2021, where Input1 represents the number of nucleic acid tests per thousand people, Input2 represents the vaccine doses per thousand people, and Input3 represents the strict index, as shown in Table III.

TABLE III
REDUNDANCY OF PREVENTION AND CONTROL INPUT IN 14 COUNTRIES

Country	2020			2021		
	Input1	Input2	Input3	Input1	Input2	Input3
Australia	—	—	—	—	—	—
Canada	38.07	0.59	—	—	—	—
France	271.46	—	—	1179.72	213.68	—
Germany	—	—	—	—	24.29	—
India	87.88	—	37.52	—	—	—
Italy	72.64	—	—	808.69	60.40	—
Japan	—	—	—	121.22	449.66	—
Mexico	—	—	—	—	—	—
Russia	365.54	3.53	—	—	—	—
Korea	37.73	—	—	—	—	—
Thailand	—	—	—	136.76	187.12	—
Turkey	252.08	—	29.74	—	—	—
UK	573.28	—	11.30	3742.69	426.45	—
USA	323.40	12.80	—	—	—	—

As shown in Table III, Australia and Mexico did not have input redundancy for two years. In 2020, only six countries had input redundancy: Canada, India, Russia, South Korea, Turkey and the United States. This indicated that these six countries have taken positive measures in epidemic prevention and control to improve the efficiency of factors so that there was no redundancy in the following year. For example, Canada could achieve relative optimality by reducing nucleic acid testing by 38.07 units per 1000 people and vaccination by 0.59 units per 1000 people.

In terms of nucleic acid tests, France, Italy, Japan, Thailand and the United Kingdom all had excessive spending. Among them, the input redundancy in Italy increased from 72.64 to 808.69, with a growth rate of 1013%. The main reason was that in the early stage of COVID-19 outbreak, the Italian government misjudged the severity of the epidemic and failed to detect and isolate the infected people in a timely manner, thus causing the fluctuate situation. And Italy, the epicenter of the COVID-19 outbreak in Europe, has had to invest heavily in nucleic acid testing to find people infected with virus.

In terms of vaccinations, France, Germany, Italy, Japan, Thailand and the United Kingdom all transitioned from having no redundancies to having redundancies. This was due to the fact that COVID-19 vaccination was not widespread in the early stage and required 2-3 shots per individual, with a long vaccination cycle. Therefore, there was a certain lag in preventing the spread of the virus.

In terms of the strictness index, most countries did not exhibit redundancy. Only India, Turkey, and the United Kingdom demonstrated some degree of redundancy in 2020, suggesting that these three nations need not be excessively stringent in their management of prevention and control policies.

Based on the above findings, this study posits that the efficacy of epidemic prevention and control is not solely contingent upon the quantity of input; rather, it is imperative to enhance the efficiency of factor input.

V. RESEARCH CONCLUSIONS AND RECOMMENDATIONS

The COVID-19 pandemic has been ongoing for three years, imposing significant socio-economic costs and challenging medical and health systems of countries. By selecting reasonable and quantifiable input-output indicators, the DEA method was used to analyze the epidemic prevention and control efficiency of 14 countries in 2020 and 2021, revealing that there still exist 42.86% of countries were ineffective in epidemic prevention and control.

Based on the previous analysis, this study considers the following questions: Firstly, it was observed that a stricter prevention and control policy does not necessarily result in better control effectiveness as evidenced by Japan's 2020 strict index of 34.48 compared to the United States' index of 59.58, yet Japan exhibited relatively superior prevention and control efficiency. Similarly, in the per capita cost index designed in this study, the United States had a per capita cost of 4433.93 yuan in 2020, while Japan's was only 1118.33 yuan. Therefore, it can be inferred that stringent management policies may not prove effective against sudden epidemics and could potentially result in social and economic costs.

Some scholars also confirm this conclusion, arguing that highly restrictive policies have huge social and economic costs (Coccia 2023). Second, through redundancy analysis of the input, we have discovered that more vaccinations do not always better. Despite its relative efficiency, Japan had a surplus of 449.66 vaccine doses per 1,000 people in 2021, which represents an inefficient allocation of medical resources towards vaccination. In the study on vaccination, some scholars conclude that the average level of administering about 80 doses of vaccines per 100 inhabitants between countries can sustain a reduction of confirmed cases and number of deaths (Coccia 2022). Finally, developed countries with ample medical resources may be less efficient than developing countries. For example, India achieved an efficiency growth rate of 76.06% and reached the effective state, while the developed countries such as Canada, France and Germany were remained ineffective. This study posits that the efficacy of epidemic prevention and control is influenced by a multitude of factors. India boasts a relatively youthful population, which has played an instrumental role in mitigating the impact of epidemics. However, it must be noted that adequate medical resources are indispensable for pandemic preparedness.

There were several limitations in this study. Firstly, only 14 countries were selected as samples to measure the prevention and control efficiency, and more countries should be included to support the research results. Secondly, the selection of indicators does not cover all the factors that could affect the spread of COVID-19, such as medical reserve resources. For some variables, Inconsistencies in statistical methodologies across countries and fundamental differences between them also preclude achieving sample homogeneity. In addition, various countries reported the number of confirmed cases, nucleic acid tests and vaccinations, and the conclusions were reached only by analyzing the reported data in this paper. Finally, the United Nations' national happiness index, which is based on Gallup polls, may be subject to some degree of subjectivity.

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