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Time-series COVID-19 policy outcome analysis of the 50U.S. states

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ABSTRACT

Goal of health policies is to protect and promote the health of communities. We examined COVID-19 policy outcomes of the 50 US states according to policymaker assumptions over time. With daily cumulative population mortality chosen as an indicator to evaluate and score outcomes of individual health policies, Hawaii had the best score and Arizona has the worst score. Our policy outcome analysis tool could identify and quantify policymakers' faulty assumptions against COVID-19, and concludes that the more COVID-19 deaths, the greater the economic loss.

Introduction

The goal of health policy or preventive medicine is to protect and promote the health of individuals and the community [1]. The worst consequence of poor health is death. In other words, the number of deaths due to a disease is a good indicator to debate the health indicators in health policy from the viewpoint of policy outcome analysis, not general policy analysis. The number of deaths due to a disease per population is a mortality rate.

A literature review was conducted on health policy analysis of COVID-19. Many health policy experts have explicitly stated that the policy outcome analysis of COVID-19 is premature, but they are downplaying the progress and evolution of COVID-19 over time.

There are two mitigation approaches such as pharmacological approach such as vaccination and non-pharmacological approach [2] such as the mandatory test-isolation. The test-isolation strategy is one of the best mitigation methods, to test and identify infected individuals at an early stage and to isolate them from uninfected people during the quarantine period. Therefore, policymakers can control tests and the quarantine period. The longer the quarantine period the less the COVID-19 spreads. The shorter the quarantine period, the more the COVID-19 spread. It was discovered that the mandatory test-isolation policy can completely suppress and mitigate the COVID-19 pandemic [3,4].

Based on the result of a literature review, a time-series policy outcome analysis of COVID-19 was not conducted due to controversy over the selection of impact indicators or influence determinants. This paper is not a policy analysis, but rather an analysis of the health policy outcomes of the 50 US states in COVID-19. Evaluating the health policy outcomes plays a key role in identifying and quantifying when the policy made faulty assumptions over time. In other words, it is possible to identify when and quantify how large the policymaker's insufficient considerations were.

The daily cumulative population mortality or score is the number of daily cumulative deaths due to a COVID-19 disease per population [5]. The lower the score, the better the policy. The better the policy, the lower the population mortality rate. Therefore, scoring individual policies is based on the single indicator: dividing the number of daily cumulative COVID-19 deaths normalized by the population in millions. In this paper, the daily cumulative population mortality was chosen as one indicator because higher scores indicate greater unhappiness and lower scores indicate less unhappiness in order to achieve the goal of health policy [1].

There are two types of health policy analysis: snapshot analysis and time-series analysis [6]. Time series analysis is superior to snapshot analysis. This is because time-series analysis can express the process of transition and progression over time, while snapshot analysis cannot. In other words, time-series policy analysis allows policymakers to identify and quantify when they made faulty assumptions. It is essential for health policy experts to investigate the time-series policy outcome analysis of COVID-19.

Chyon et al. presented time series analysis and predicting COVID-19 affected patients [7]. However, they did not compare their result with others. The comparison between policy outcomes of 50 US states plays a key role in revealing which US states are handling well against COVID-19. In other words, their method cannot be used for COVID-19

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policy outcome analysis.

Cho et al. studied effect of social distancing on injury incidence during the COVID-19 pandemic [8]. However, their method is not applicable to the analysis of COVID-19 policy outcomes due to its lack of generalizability.

Wang et al. investigated prediction and analysis of COVID-19 daily new cases and cumulative cases [9]. However, their method is not suitable for analyzing COVID-19 policy outcomes due to the higher level of uncertainty associated with case numbers compared to the number of deaths.

Singh et al. conducted time series analysis of COVID-19 data to study the effect of lockdown and unlock in India [10]. Their approach can be used for COVID-19 policy outcome analysis, but their current method cannot be directly used. For this investigation, their method would need to undergo significant updates.

Longato et al. studied time-series analysis of multidimensional clinical-laboratory data for revealing trajectories of COVID-19 outcomes [11]. The comparison between policy outcomes cannot be achieved by their method.

Navazi et al. investigated the effect of the Ontario stay-at-home order on Covid-19 third wave infections [12]. Their approach can be used for policy outcome analysis, but the comparison between policy outcomes cannot be directly calculated by their method.

Jahn et al. studied sustainable policy performance and types of governance [13]. However, they did not analyze and quantify policy outcomes.

state	deaths	population	score
Hawaii	1762	1.455	1210
Vermont	791	0.643	1230
Utah	5206	3.272	1591
Alaska	1408	0.733	1920
Washington	15170	7.705	1968
District of Columbia	1411	0.69	2044
Maine	2824	1.362	2073
New Hampshire	2873	1.378	2084
Oregon	9029	4.237	2130
Colorado	13918	5.774	2410
Nebraska	4884	1.962	2489
Minnesota	14357	5.706	2516
California	101322	39.538	2562
Maryland	16114	6.177	2608
Virginia	22825	8.631	2644
Wisconsin	15931	5.894	2702
North Carolina	28917	10.439	2770
Idaho	5334	1.839	2900
Illinois	40747	12.813	3180
North Dakota	2479	0.779	3182
Texas	92874	29.146	3186
Delaware	3218	0.99	3250
Connecticut	11803	3.606	3273
Iowa	10465	3.19	3280
Massachusetts	23097	7.03	3285
Montana	3640	1.084	3357
Kansas	9913	2.938	3374
Wyoming	1959	0.577	3395
Rhode Island	3820	1.097	3482
Ohio	41189	11.799	3490
South Dakota	3144	0.887	3544
Georgia	40071	10.712	3740
Indiana	25470	6.786	3753
Pennsylvania	49119	13.003	3777
Missouri	23348	6.155	3793
South Carolina	19426	5.118	3795
New Jersey	35614	9.289	3833
Nevada	11917	3.105	3838
New York	78198	20.201	3870
Florida	84176	21.538	3908
Kentucky	17789	4.506	3947
Louisiana	18394	4.658	3948
Michigan	40836	10.077	4052
Oklahoma	16093	3.959	4064
Tennessee	28305	6.911	4095
New Mexico	8870	2.118	4187
Arkansas	12729	3.012	4226
Alabama	21263	5.024	4232
West Virginia	7843	1.794	4371
Mississippi	13145	2.961	4439
Arizona	32311	7.152	4517

Fig. 1. Result of usscore as of Jan. 9, 2023.

Health policy outcome analysis is essential for policymakers to identify, quantify and correct their faulty assumptions in policies. A time-series COVID-19 policy analysis tools, uscovid is introduced in this paper using the US dataset. The uscovid tool is a Python Package Index (PyPI) application to run on Windows, MacOS, and Linux operating systems as long as Python is installed on the system. This paper will reveal what is going on in the 50 US states from the COVID-19 policy outcome viewpoint. The calculation in uscovid is based on the daily population mortality rate: dividing the number of COVID-19 cumulative deaths by the population in millions.

The contribution of this paper lies in that this is the original 50 US-states policy outcome analysis. The time-series policy outcome analysis tool, uscovid will visualize the progress of policy outcomes and discover many facts on COVID-19 in the US.

Methods and results

A snapshot of COVID-19, a policy outcomes analysis tool for the 50U. S. states, is called the "usscore," which is the cumulative total number of COVID-19 deaths in each state divided by the state's population in millions. In other words, scoring individual states is calculated based on dividing the total cumulative deaths by the state population which is called the population mortality rate [14]. The lower the score, the better the policy.

The number of daily cumulative COVID-19 deaths by state is automatically scraped over the Internet. The advantage of the snapshot scoring tools such as usscore can reveal the best policy in the 50 states of the US.

The usscore tool is a PyPI application which runs on Windows, MacOS, and Linux operating systems as long as Python is installed on the system. Before running the usscore tool, install Python on the system. In order to observe the snapshot of other countries from the worldwide perspective, use the PyPI scorecovid tool [4]. Fig.1 shows the snapshot outcome of the 50 states of the US. In order to run usscore, type the following pip command for installing usscore and run it. ($) character indicates the prompt of the system terminal.

$ pip install usscore

Then, type the following command.

$ usscore

Fig. 1 shows the result of usscore as of Jan. 9, 2023. Hawaii has the best score of 1210 and Arizona has the worst score of 4517. We must know and compare these results with other countries with scorecovid. The scorecovid tool is also a PyPI application. Fig.2 shows the result of 15 countries with scorecovid. Japan has the best score of 469 and Hungary has the worst score of 5025.

Time-series COVID-19 policy outcome analysis tool, uscovid is newly proposed in this paper. One advantage of time-series policy outcome analysis tools, such as uscovid, is their ability to visualize and identify instances where policymakers may have made incorrect assumptions about COVID-19. This can help inform the correction of current policies to reduce unnecessary deaths.

The policy outcome is calculated by the single indicator: daily cumulative population mortality over time. The daily cumulative population mortality or scoring is based on dividing the number of daily cumulative COVID-19 deaths by the population in millions over time. The lower the score, the better the policy. The higher the score, the unhappier we are.

Time-series analysis allows policymakers to identify and quantify when they made faulty assumptions or behavior changes of the communities. Remember that, this is not a policy analysis, but a policy outcome analysis.

In order to run uscovid, type the following pip command after installing Python on your system.

$ pip install uscovid

To investigate Hawaii and Arizona, run the following command.

$ uscovid Hawaii Arizona

country	deaths	population	score
Japan	59423	126.48	469.8
New Zealand	2331	4.82	483.6
South Korea	32590	51.27	635.7
Taiwan	15506	23.82	651
Iceland	229	0.34	673.5
Australia	17304	25.5	678.6
Canada	49542	37.74	1312.7
Israel	12079	8.66	1394.8
Germany	162688	83.78	1941.8
Sweden	22142	10.1	2192.3
France	162719	65.27	2493
United Kingdom	213966	67.89	3151.7
Brazil	694779	212.56	3268.6
United States	1096503	331	3312.7
Hungary	48546	9.66	5025.5

Fig. 2. Result of scorecovid as of Jan. 7, 2023.

The result will be displayed on the screen. Fig.3 shows the generated uscovid result with Hawaii (best score) and Arizona (worst score) as of Jan. 7, 2023. In Fig.3, the vertical axis on the left side shows the score or the population mortality for each state and the horizontal axis indicates the date of the score while that on the right side indicates the first order differential value that represents the faulty assumption magnitude. The lower the score, the better the policy. The larger the faulty assumption magnitude, the worse the policy.

Scores always monotonically increase because the number of cumulative deaths does not decrease. The size of a bar quantifies a faulty assumption by policymaker. The larger the bar, the unhappier the people. In other words, uscovid can provide a happiness or unhappiness index of COVID-19. The lower the score or the bar, the better the policy. The lower the score or the bar, the less unhappy we are.

Discussion

A literature review was conducted on health policy outcome analysis of COVID-19. The result shows that there is no quantified analysis of health policies on COVID-19. This paper presented the snapshot COVID-19 outcome analysis and time-series COVID-19 outcome analysis of the 50 states of the US. The time-series COVID-19 outcome analysis can provide us the progress and the transition of COVID-19 in the US. The first order differential of data can detect the peak points in every wave in COVID-19. The uscovid tool can identify and quantify when policymakers made faulty assumptions or behavior changes of the communities with COVID-19 variants in individual states of the US.

In order to mitigate and reduce the unnecessary deaths due to COVID-19, we need to carefully monitor what is going on about the outcome of COVID-19 and control the robust and rational policy. This paper introduced health policy outcome analysis tools such as scorecovid for scoring individual countries, usscore for evaluating individual state policies, and newly proposed uscovid for time-series policy outcome analysis of the 50 states of the US. The introduced tools such as usscore, uscovid and scorecovid can reduce unnecessary COVID-19

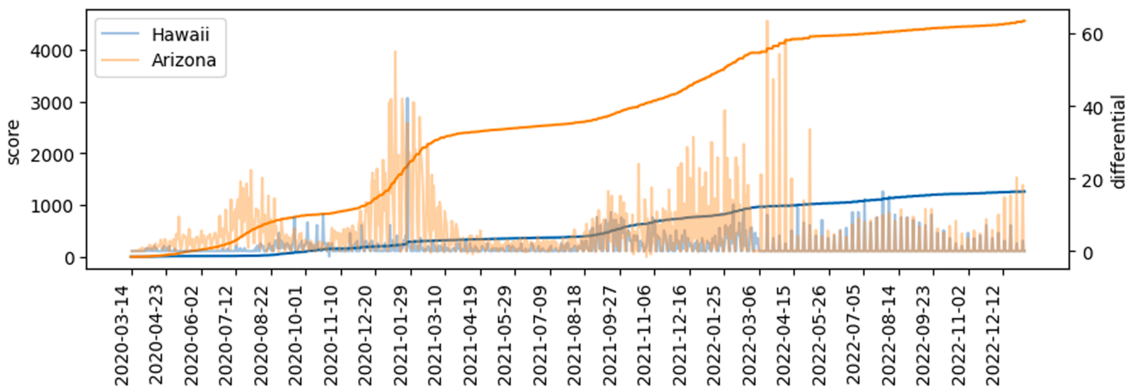

Fig. 3. Result of uscovid with Hawaii and Arizona as of Jan. 7, 2023.

deaths because policy faulty assumptions or behavior changes of the communities with COVID-19 variants by comparing performance of individual policies among 50 states and other countries can be corrected by observing the policy outcome.

The jpscore tool revealed that Niigata prefecture in Japan has the best score not only in Japan but also in the world. Niigata has the strongest herding behavior [15,16]. Japanese people wear face masks at all times, with or without warning from the government. The policy outcome is heavily affected by the general public's behavior in Japan.

Conclusion

Both tools such as usscore and uscovid are based on the population mortality: dividing the number of daily cumulative COVID-19 deaths by the population in millions. The usscore tool is to generate a snapshot list of sorted scores by state in the US where the score represents the population mortality. The time-series uscovid tool allows policymakers to identify and quantify when they made faulty assumptions over time. The usscore tool is intended to be used by policymakers to learn good strategies from states with superior scores. The time-series uscovid policy outcome analysis tool can visualize and monitor the progress of the effectiveness over time. Faulty assumptions in policies can be identified and corrected by policymakers through visualizing the time-series scores.

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Ethical approval

Not required.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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