1. Introduction

In Mar 2020, COVID-19, also known as Coronavirus Disease, was declared as a pandemic by the World Health Organization. Since then the world has seen 2.3 million deaths and 103 million cases of the virus worldwide with the impact varying across countries.

2. Problem Definition

In this study, we aim to understand what factors contribute to the spread and containment of COVID-19, by exploring the two topics: 1) the correlation between countries' development indicators and their pandemic situations, and 2) the differentiating success factors in controlling the spread of the virus. Through data analysis and visualization on COVID cases and deaths, countries' development indicators, and control and containment measures, we hope to shed some light on factors correlating with the transmission, mortality, and control of COVID-19, and also provide some lessons learnt for governments, world organizations, and even the entire human race.

3. Survey

For COVID-19 tracking (cases, death toll, and vaccination progress), various tools and sources are available. The New York Times has a variety of charts to illustrate the current vaccination data (Holder, 2021). A study (Guihong Fan, 2020) conducts time-series studies to track and compare the trend of the case fatality rate of COVID-19 in the first and second COVID waves. **For COVID-19 trend analysis**, several studies have investigated factors affecting pandemic spread and containment. (Allel, 2020) studies country-level factors related to cumulative cases of COVID-19 in the early stage using linear regression models. (Dharun Kasilingam, 2020) combines exponential growth models and various machine learning techniques using countries' infrastructure, policies as independent factors to predict COVID-19 trends. (Giangreco, 2020) uses regression models to examine the hypothesis that the spread of COVID-19 correlates to social behaviors. The analysis methods employed in these studies are a good benchmark for our analysis. **For COVID-19 containment and vaccine analysis**, Oliver et al. (2021) focuses on studying characteristics of the vaccine itself. Coronavirus calculators created by a Polish company (2021), Launch and Scale Speedometer established by Duke Global Health Innovation Center (2021) cover models and variables about analyzing vaccine administration, procurement, and manufacturing progress. A few location-specific studies focus on the effects of vaccination in conjunction with Nonpharmaceutical Interventions (NPIs). (Paltiel A.D., et.al., 2020) (Saad-Roy,et al., 2020) A North Carolina study used a simulation varying the presence of NPIs, different levels of vaccine coverage, and efficacy studying their impact on infections, hospitalizations, and deaths (Patel M. D.,et.al., 2020).Similarly, the UK studies simulated the rollout of vaccines together with the lifting of NPIs (Moore S.,et.al., 2020) (K., 2020). These studies fail to account for other intervening factors such as governance, country development, NPIs compliance, as well as the type of NPIs. (Daniel M., et al., 2020) The data quality varies by country depending on data collection methodology and bounded by case testing capacity.

4. Proposed Method

4.1 Intuition (why should it be better than the state of the art?)

Our approach is global and comprehensive compared to current studies. We examined the pandemic from two angles: **spreading and containment**. Inspired by Mirzaei (2011) and Islam (2018), we classified countries into multiple groups to examine the relationship between development indicators and the severity of COVID-19 impact. In addition to regression used in (Allel, 2020), we experimented with various machine learning techniques such as Decision Tree to investigate factors affecting COVID-19 spread. **For containment** analysis, we studied the trend and effectiveness of vaccines, built a prediction model and dashboards for data visualization. We examined NPIs, accounting for the country differences instead of measuring the effectiveness in one specific location (Kabesch, et al., 2020). Also, we analyzed the combined effect of NPIs and vaccinations with regards to the number of infections globally, ranked the effective NPIs (Xiao, et al., 2020), and predicted the impact of vaccination in reducing spread. Compared with the currently referred COVID cases tracking projects, our study provided more aspects like vaccine progress and NPIs. By integrating multiple datasets, our dashboard provides a holistic view of spread and containment insights with interactive toolbars and animation by location and time.

4.2 Methods and Approaches: algorithms, user interfaces

4.2.1 Data Collection & Preparation

Country development indicator data are obtained from the World Bank online data portal and COVID-19 daily cases and vaccine data is obtained from Kaggle and Our World in Data. US and EU vaccine progress data are collected from CDC COVID data tracker and ECDC COVID vaccine tracker. Dataset for NPIs implemented by governments are collected by ACAPS.

51 indicators covering countries' economy, healthcare, education, infrastructure, and demographics are selected for modeling. We prepared 4 sets of data to represent country development status, including absolute values, three-year moving average of absolute values, YOY percentage change of development indicators and three-year moving average of YOY percentage change of development indicators in 2018. Total cases, infection rate, death rate and day interval of COVID-19 peak-and-trough are selected to measure COVID-19 spread.

For vaccine progress analysis, we used linear interpolation to make imputations for the missing data. More data dimensions including age group distribution are added for trend analysis for the US states and EU countries. Considering there might be a large amount of imputed data and variance in daily increment of doses administered, we calculated the seven-days moving average and used the recent vaccination rate to predict when a significant level of immunity can be achieved for the selected country.

To analyze the effect of NPIs in reduction of active cases, we combined the NPIs dataset with aggregated monthly COVID daily active cases. A joined dataset contains factors including six NPI categories, GDP per capita, Human Development Index(i.e. HDI is an index that measures a long and healthy life, access to education and a decent standard of living)(Roser, M., 2019), average stringency index (i.e. stringency index is based on nine response indicators)(Our World in Data, 2021), monthly new cases per million capita to examine the NPI effectiveness for 193 countries. The different brands of vaccines data were joined to examine the effectiveness of each brand.

4.2.2 Models

For COVID development across countries, K-Means clustering was performed to group countries based on COVID development from Feb 2020 to Mar 2021 and development indicators. Regression, Decision Tree and Random Forest were used to explore the potential relationship between country development indicators and COVID development. Pearson correlation analysis was performed to examine the relationship between the factors in NPI dataset. A decision tree model was used to analyze the trend of various variables against the new COVID cases smoothed per million.

4.2.3 Data Visualizations

We chose Tableau as the user interface. A comprehensive world map with filter options, color legends and tooltips are used to demonstrate the cases spread situation, vaccine distribution and NPI implemented across location and time. Line charts with countries and dates as filter options are used to show vaccination progress and trends of NPI implementation. A tree map was done to visualize the hierarchy of NPI categories and measures. All graphs and charts are provided with interactive toolbars.

5. Experiments/Evaluation (List of Innovations)

5.1 Exploratory Data Analysis (EDA)

Exploratory data analysis show that different regions exhibit different COVID-19 case and death patterns, countries in the same region but of different income groups also display differing COVID trends. For example, high income level countries occupy most of the vaccine resource, having a vaccine coverage and administered rate higher than lower income countries. Both US states and EU countries tended to prioritize vaccine coverage for the elderly. From the country level, regardless of total vaccination or daily vaccination administered, the US and China are the top two countries among the current country data available. It is worth noting that India, the only low-middle-income country to have developed a vaccine, also has a high level of vaccination rate in terms of daily dose administered.

5.2 Clustering of Countries

Clustering by Number of COVID-19 Cases and Deaths

K-means clustering was used to divide countries into groups. The elbow method was used to choose the optimal number of clusters k. We performed two clustering models. The first model, we clustered the total number of COVID-19 cases and deaths, which grouped the countries into four clusters: cluster 1 consists of United States alone with much higher number of cases and deaths, cluster 2 consists of Brazil and India, cluster 3 consists of 17 countries such as France, Germany, Indonisia, Spain, UK, etc. Cluster 4 contains the remaining 156 countries. However, the total number of cases and deaths might be affected by a country's population. Thus, the second clustering model was done using population normalized number of cases and deaths. The countries were grouped into five clusters. The cluster profile varies significantly: cluster 1 with the highest normalized number of cases and deaths consists of Czech Republic and Montenegro. The US falls into cluster 2 along with Spain, Sweden, and other 13 countries, mostly European.

The cluster profile is dynamic. To study how countries move from one cluster to another over time, clustering was run on quarterly COVID data. We visualized the changing clusters over time in our dashboard. (Only the first two clusters were listed for illustration)

Period	Cluster 1 Countries	Cluster 2 Countries
2020 Q1	Spain, United States	China, Germany, Italy
2020 Q2	United States	Brazil
2020 Q3	India, United States	Brazil
2020 Q4	United States	Brazil, France, India, Italy, Russia, United Kingdom
2021 Q1	United States	Brazil

Clustering by development indicators

In order to study the impact of development indicators on COVID development using data of similar distribution for better model performance, the same clustering method was applied to absolute values of development indicators in 2018 for each country. Three clusters were identified with the elbow method for K-means clustering. The cluster profile is highly unbalanced, whereas top influencing countries like the US and China belong to one group, and more developed or leading emerging countries fall within one group. This result led to insufficient data of each cluster group for modelling in the next step. Hence, cluster-wise modelling to identify relationships between development indicators and COVID development was no longer adopted.

5.3 Relationship between development indicators against COVID development

Various machine learning models were used to explore the potential relationships between country development indicators and COVID development. Multiple regression set-ups using different data engineering methods were experimented in the study. Non-linear models such as Decision Tree and Random Forest were also explored.

Pearson correlation: a quick correlation analysis was conducted before modelling in order to give us some indications on potential relationship between development indicators and various COVID development metrics. For total cases, *GNI (current US$)* and *Goods Imports* are more positively correlated with *Total infected cases*, with correlation coefficients higher than 0.65. For infection rate, multiple indicators such as *Access to electricity (% of population), Births attended by skilled health staff (% of total), Individuals using the Internet (% of population), Physicians (per 1,000 people*) are moderately positively correlated with infection rate, with correlation coefficients ranging between 0.40 to 0.60; Fertility rate, total (births per woman) and Mortality rate, infant (per 1,000 live births) are negatively correlated with infection rate.

Regression with PCA: We applied PCA on all 51 development indicators and used two principal components as independent variables for linear regression. The achieved adjusted R squared of 0.229 was not satisfactory. Two components are insufficient to explain the variance of total infected cases across the world. In addition to poor interpretability, we stopped using PCA for our modelling.

Regression after collinearity check: For development indicator pairs with absolute correlation coefficients larger than 0.7, only one indicator was kept. Among models with different combinations of input and output variables, the *three-year moving average values of development indicators* in 2018 against *total infected cases* model reaches the highest adjusted R^2 of 0.626. Better *Access to electricity (% of population)*, higher *GNI (current US$)* and higher *School enrollment, primary (% gross)* related positively to more COVID cases.

Stepwise regression: Out of the 51 pre-selected country development indicators, we chose one indicator at a time to try to improve the regression model. In the end, 19 indicators out of the 51 indicators with *absolute values in 2018* were selected to model against *total infected cases*. *GNI (current US$), School Enrollment - primary (% gross)* are positively related to total COVID cases; *Gross domestic savings (current US$)* is negatively associated with total infected cases. The achieved adjusted R squared of 0.839 outweighs all other models.

Decision Tree: Together with 10 fold cross validation, we applied Decision Tree on the prepared independent variables and dependent variables. Across all models, average scores (R^2 of the prediction) of cross validation are all negative, indicating that Decision Tree is not an appropriate model under this use case.

Random Forest: This method was used as an alternative to the decision tree, to overcome the limitations of the previous method. *Development indicators* in 2018 against *total infected cases* model reaches OOB score (R^2 on unseen data) of 0.28, highest among all Random Forest models. Top 5 most important features are *GNI (current US$), Gross domestic savings (current US$), Population growth (annual %), Birth rate, crude (per 1,000 people)* and *Compulsory education, duration (years)*. Yet, the score of 0.28 reflects a weak explanatory power of development indicators on COVID cases.

From all model results, more developed countries with more advanced economic development, wider education coverage and better infrastructure support tend to have more infected cases. Possible reasons could be that more developed countries have more extensive testing, more comprehensive recording systems, higher population density, larger population movement supported by better transportation infrastructure. However, as reflected in various model performance scores, development indicators alone are unable to explain COVID development well and important explanatory variables are not included here.

5.4 Simple Moving Average model to predict time to achieve herd immunity

As pointed out by the World Health Organization experts, a 65%-70% vaccine coverage rate is a way to reach population immunity through vaccination (Burger, L. & Kate, K., 2020). In our model, we set a 70% vaccine coverage rate (two doses) as herd immunity threshold for each country and used the latest moving average of daily doses administered to predict remaining days till herd immunity was achieved.

In addition, we found that there was a correlation between the number of days to herd immunity and country income level: for most high-income level countries, vaccination campaigns could be completed within one or two years. However, it was interesting to note that for a vaccine acceptance survey conducted among 31 countries by Oliver et al. (2021), countries with a high acceptance rate, such as Vietnam, India and China have a contradictory result in number of days to herd immunity. Since the number of days to herd immunity is calculated by dividing 2 doses for 70% of the population by daily vaccination rates, for China and India with high daily vaccination rates, we deduced that these results might be affected by the large population in these countries.

5.5 Pearson correlation analysis among NPI categories and COVID-19 cases
We experimented with various NPI categories and monthly new cases per million capita. We also added development indicators like GDP per capita, HDI and average stringency index.

We plotted heatmaps for correlation analysis and observed negative correlation between most NPI categories and monthly new cases per million capita, positive correlation between cases and average stringency index. For the USA, the movement restrictions category is most negatively correlated with cases. For China, the social distancing category is most negatively correlated with cases. Drilling into these categories, we learnt that border closure, curfews, VISA restrictions were the top three implemented measures in the movement restrictions category and closure of businesses and public services in the social distancing category was the measure implemented most number of times across the globe. We also visualized the Pearson coefficients in a graph network diagram by applying Python's networkx library. The factors were displayed in spiral graph layout which coefficient values were filtered to be greater than +/- 0.1. In the graph network, we could see that average stringency index and movement restrictions are the factors relatively more correlated to the number of cases. Furthermore, the countries with GDP per capita and high HDI generally implemented more measures in NPI categories. This model can be easily applied to analyze those factors which are highly correlated between country level indicators and NPIs implemented.

5.6 Decision Tree Regression on Vaccination and NPIs against COVID-19 cases

We further expanded the variable sets and modelled them against new COVID-19 cases. Variables included HDI, stringency index, GDP per capita, new vaccinations smoothed per million (by 7 day moving average), hospital beds per thousand, population density diabetes prevalence, the proportion of population aged 65 and older, cardiovascular death rate.

We noted that the top 3 most important factors in predicting new cases were stringency index, new vaccinations smoothed per million and GDP per capita. The decision tree path showed that a higher stringency index together with a higher vaccination rate led to lower numbers of new cases. This indicates that NPIs work together with vaccinations to decrease the numbers of new infections (as confirmed from the trends on the dashboard). Vaccine coverage was not in the top ten features, but we hypothesize that coverage had to surpass a certain percentage before being considered an important feature, with some studies placing herd immunity at 58% (Fontanet et al. 2020). The model also showed that vaccine brands were not an important factor in the model. The model yielded a high accuracy of 0.78 when tested on unseen data. This is as compared to the linear regression which had an accuracy of 0.13. Similarly when regressed against new deaths per million, the top three variables with the highest feature importance score are stringency index, aged 70 and older and new vaccinations per million, which confirms that the COVID vaccine is effective in preventing severe cases in turn more deaths. People aged older than 70 and the cardiovascular death rate are also significant being in the top 4, which corresponds to the literature that the risk of mortality is higher for older people as well as people with existing health issues (Mueller et al., 2020). Another notable mention is that population density appeared among the top 5 factors affecting new cases and new deaths.

6. Discussion & Limitation

Based on EDA and various machine learning modelling results, we observed that more developed countries, in terms of education coverage, infrastructure development and economic development, tend to have more COVID cases. Possible reasons could be developed countries have more resources to test and report cases, and might have a higher population density, also, residents enjoy better mobility with more extensive transportation networks. However, development indicators alone do not have strong explanatory powers for COVID development. In the later part of the study, we found that NPI measures and vaccination implementation affect COVID development significantly such as movement restrictions, stringency index and new vaccination smoothed per million. The analysis reinforces that higher GDP per capita leads to higher number of cases.

During the vaccine progress analysis, apart from the vaccine related data, income level was the main attribute we considered. Even though a global vaccine development, manufacture and allocation mechanism, COVAX, was established by WHO, the issues of inequality and justice around vaccine delivery still exists especially for low-income countries and non-participants of COVAX. With our vaccine coverage analysis, we hope more targeted support can be provided to some countries or regions. Another observation which had drawn our attention was the huge gap in full vaccination rate between countries. Although for countries like China, the infection rate was controlled well, the share of people received full vaccination was relatively low. As a required travel document “vaccine passport” or “e-vaccination certification of compliance for border crossing regulations” is gradually promoted globally (Mzezewa, T., 2021), increasing vaccine uptake rate is further emphasized. In order to reach herd immunity vaccination, it is important to educate the community about safety and effectiveness of vaccination.

For limitations, as the project tapped on publicly available datasets, the accuracy of data might vary by country depending on various factors, such as government transparency, data collection methodology, bounded by testing capacity (Daniel M., et al., 2020). The NPIs data lacked the date of implementation and the date of lifting the measures. The data sources could only provide the implementation date based on the news releases. Although we concluded that the number of cases change over time depending on country development, stringency of NPIs implementation and vaccination progress, we could not recommend all countries to adopt a standard containment plan. The differences between countries such as culture, demographics, warned us that it should not be a cookie-cutter approach for all. These limitations cannot be overcome unless a deeper study could be carried out for an individual country to analyze the various parameters. We hope that the study outcome will promote the acceptance of the COVID-19 vaccine.

7. Conclusion

In this study, we deep dived into COVID analysis by examining its possible relationship with country development indicators, various containment measures and their effectiveness. Our findings highlight the importance of containment measures and vaccinations to dampen COVID spread because development indicators do not have strong explanatory power for COVID development. With those findings in mind, we hope to draw more attention to support needed countries and build up the synergy to successfully conquer COVID globally.

*** All team members have contributed a similar amount of effort.**

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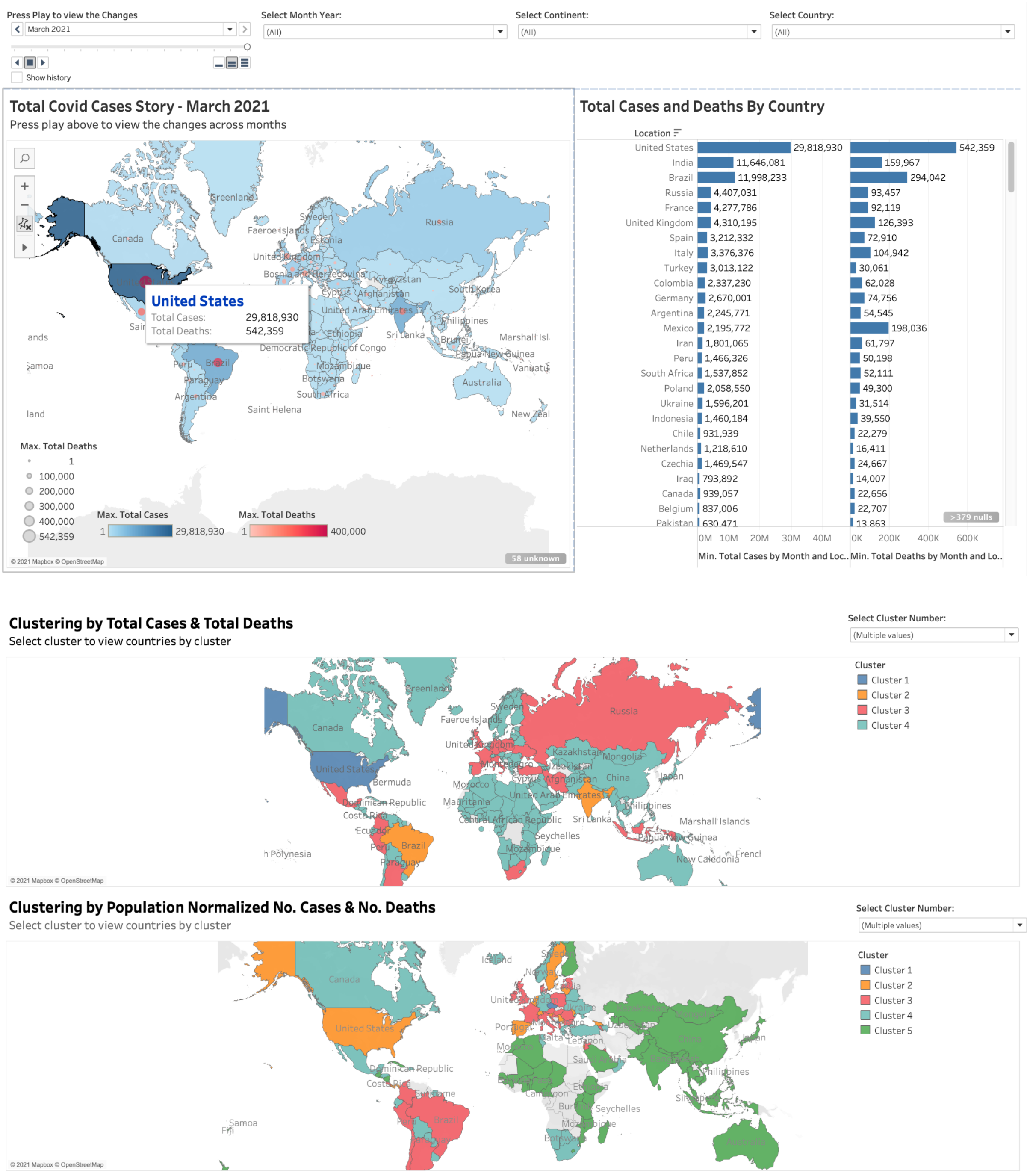
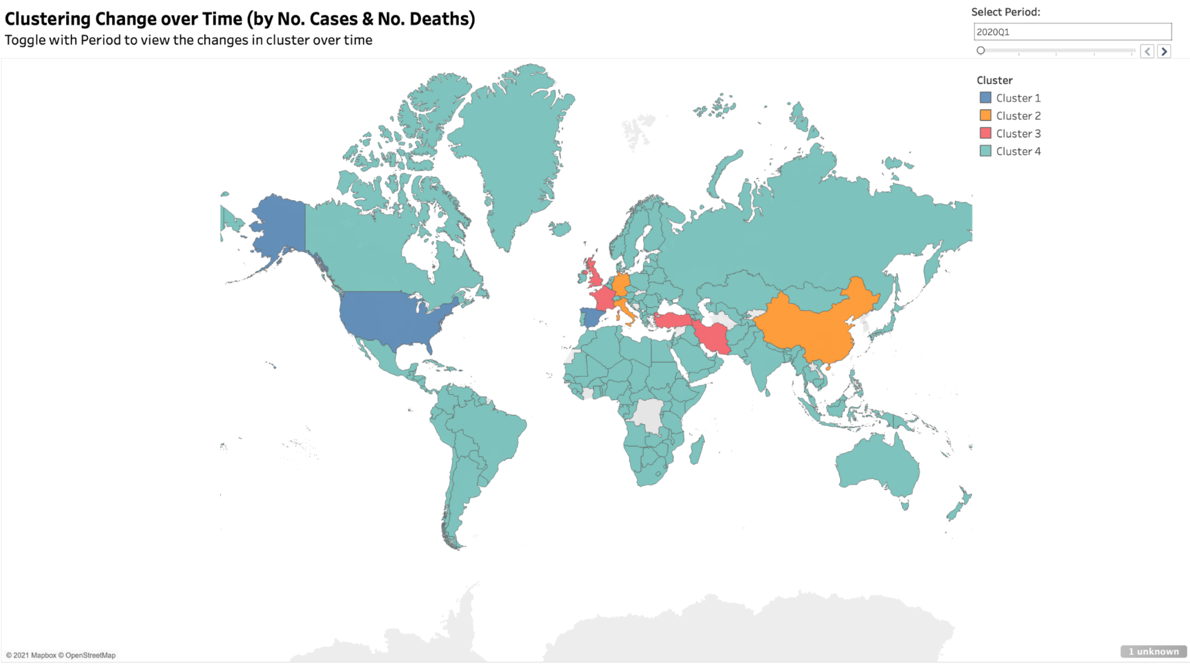
Appendix


Press Play to view the Changes
March 2021
Show history
Select Month Year:
(All)
Select Continent:
(All)
Select Country:
(All)
Total Covid Cases Story - March 2021
Press play above to view the changes across months
United States
Total Cases: 29,818,930
Total Deaths: 542,359
Max. Total Deaths
1
100,000
200,000
300,000
400,000
542,359
Max. Total Cases
1
29,818,930
Max. Total Deaths
1
400,000
© 2021 Mapbox © OpenStreetMap
58 unknown
Total Cases and Deaths By Country
Location
United States 29,818,930 542,359
India 11,646,081 159,967
Brazil 11,998,233 294,042
Russia 4,407,031 93,457
France 4,277,786 92,119
United Kingdom 4,310,195 126,393
Spain 3,212,332 72,910
Italy 3,376,376 104,942
Turkey 3,013,122 30,061
Colombia 2,337,230 62,028
Germany 2,670,001 74,756
Argentina 2,245,771 54,545
Mexico 2,195,772 198,036
Iran 1,801,065 61,797
Peru 1,466,326 50,198
South Africa 1,537,852 52,111
Poland 2,058,550 49,300
Ukraine 1,596,201 31,514
Indonesia 1,460,184 39,550
Chile 931,939 22,279
Netherlands 1,218,610 16,411
Czechia 1,469,547 24,667
Iraq 793,892 14,007
Canada 939,057 22,656
Belgium 837,006 22,707
Pakistan 630,471 13,863
>379 nulls
0M 10M 20M 30M 40M
0K 200K 400K 600K
Min. Total Cases by Month and Loc..
Min. Total Deaths by Month and Lo..
Clustering by Total Cases & Total Deaths
Select cluster to view countries by cluster
Select Cluster Number:
(Multiple values)
Cluster
Cluster 1
Cluster 2
Cluster 3
Cluster 4
© 2021 Mapbox © OpenStreetMap
Clustering by Population Normalized No. Cases & No. Deaths
Select cluster to view countries by cluster
Select Cluster Number:
(Multiple values)
Cluster
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
© 2021 Mapbox © OpenStreetMap

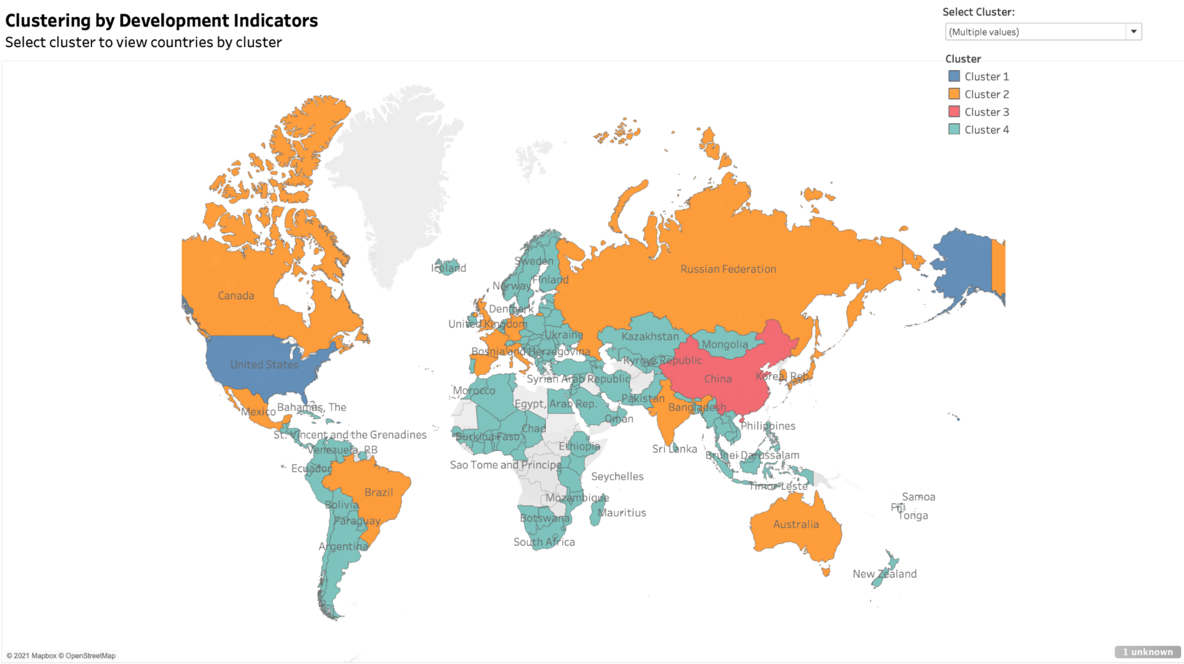
Clustering Change over Time (by No. Cases & No. Deaths)

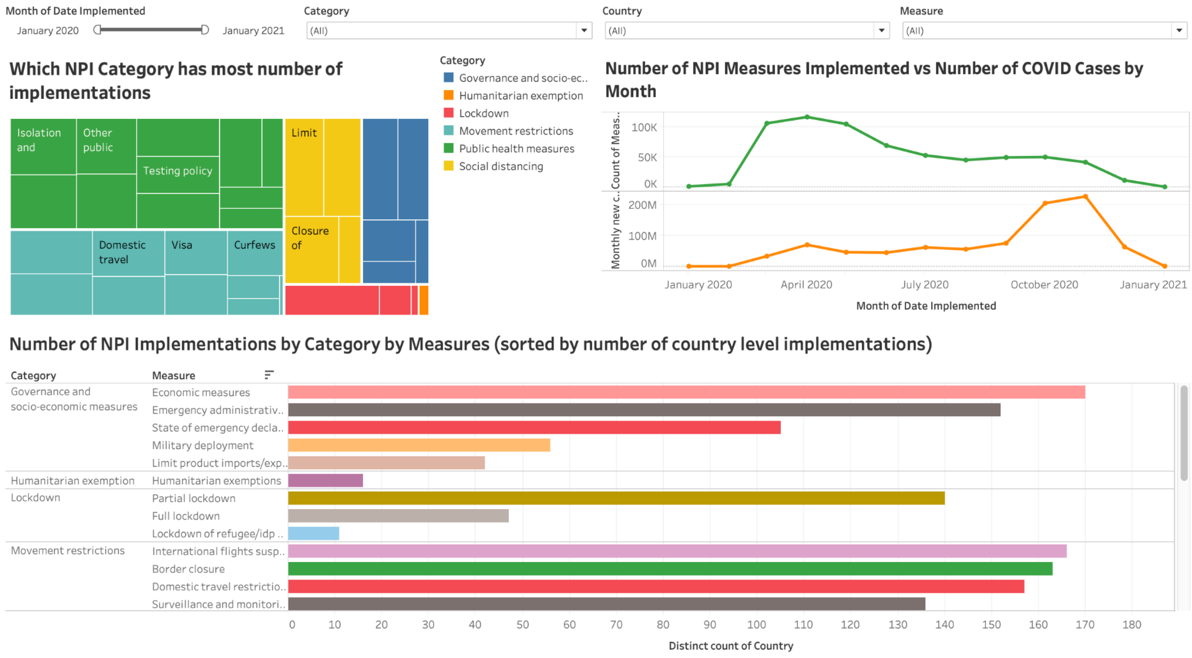
Toggle with Period to view the changes in cluster over time

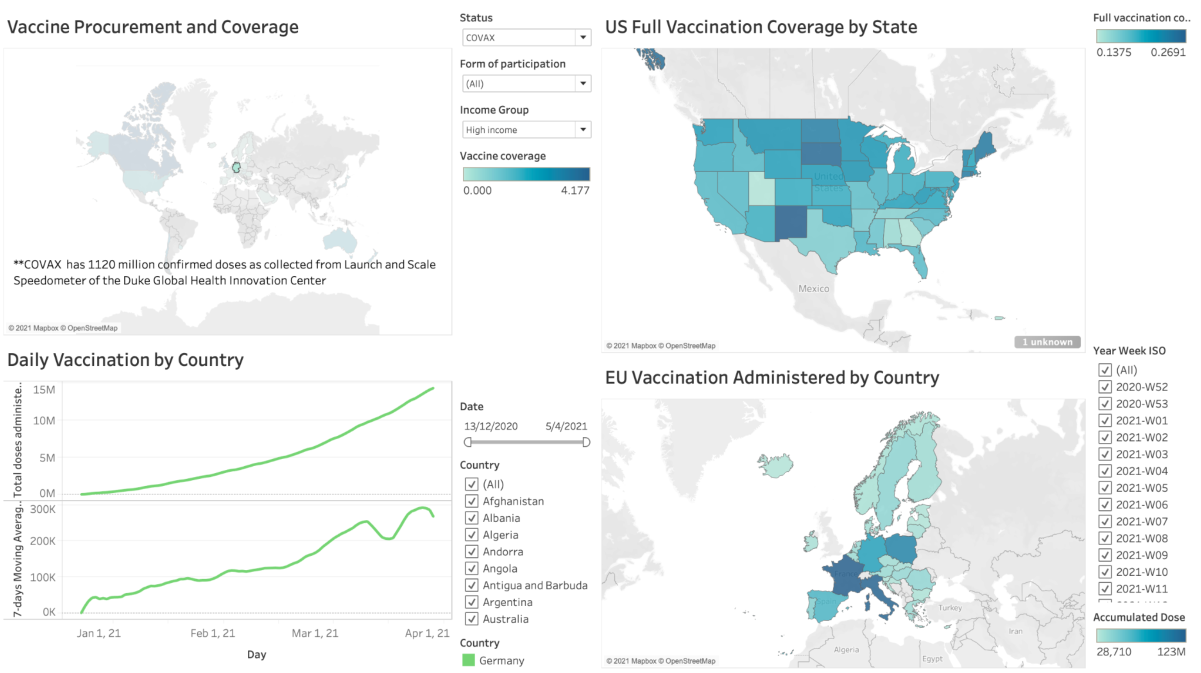


Clustering by Development Indicators

Select cluster to view countries by cluster




Month of Date Implemented
January 2020
January 2021
Category
(All)
Country
(All)
Measure
(All)
Which NPI Category has most number of implementations
Isolation and
Other public
Testing policy
Limit
Closure of
Domestic travel
Visa
Curfews
Category
Governance and socio-ec..
Humanitarian exemption
Lockdown
Movement restrictions
Public health measures
Social distancing
Number of NPI Measures Implemented vs Number of COVID Cases by Month
Count of Meas..
Monthly new c..
100K
50K
0K
200M
100M
0M
January 2020
April 2020
July 2020
October 2020
January 2021
Month of Date Implemented
Number of NPI Implementations by Category by Measures (sorted by number of country level implementations)
Category
Measure
Governance and socio-economic measures
Economic measures
Emergency administrativ..
State of emergency decla..
Military deployment
Limit product imports/exp..
Humanitarian exemption
Humanitarian exemptions
Lockdown
Partial lockdown
Full lockdown
Lockdown of refugee/idp ..
Movement restrictions
International flights susp..
Border closure
Domestic travel restrictio..
Surveillance and monitori..
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
Distinct count of Country


Vaccine Procurement and Coverage
**COVAX has 1120 million confirmed doses as collected from Launch and Scale Speedometer of the Duke Global Health Innovation Center
Status
COVAX
Form of participation
(All)
Income Group
High income
Vaccine coverage
0.000
4.177
US Full Vaccination Coverage by State
Full vaccination co..
0.1375
0.2691
Mexico
1 unknown
Daily Vaccination by Country
Total doses administe..
15M
10M
5M
0M
7-days Moving Averag..
300K
200K
100K
0K
Jan 1, 21
Feb 1, 21
Mar 1, 21
Apr 1, 21
Day
Date
13/12/2020
5/4/2021
Country
(All)
Afghanistan
Albania
Algeria
Andorra
Angola
Antigua and Barbuda
Argentina
Australia
Country
Germany
EU Vaccination Administered by Country
Year Week ISO
(All)
2020-W52
2020-W53
2021-W01
2021-W02
2021-W03
2021-W04
2021-W05
2021-W06
2021-W07
2021-W08
2021-W09
2021-W10
2021-W11
Accumulated Dose
28,710
123M
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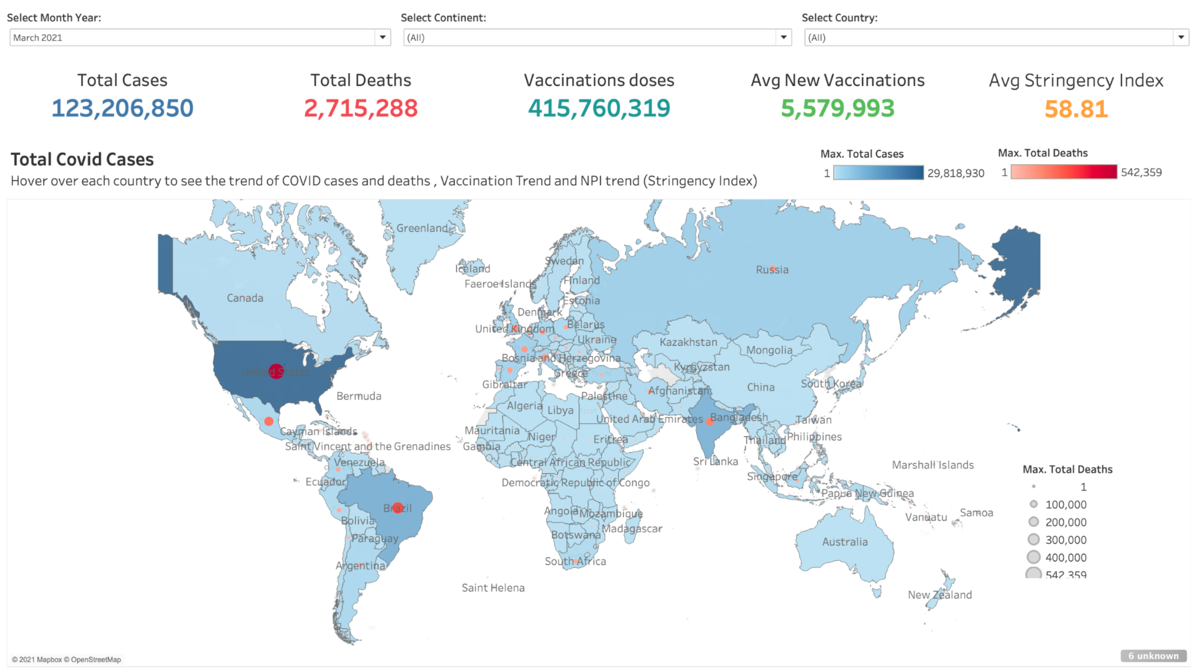
Select Month Year:
March 2021
Select Continent:
(All)
Select Country:
(All)
Total Cases
123,206,850
Total Deaths
2,715,288
Vaccinations doses
415,760,319
Avg New Vaccinations
5,579,993
Avg Stringency Index
58.81
Total Covid Cases
Hover over each country to see the trend of COVID cases and deaths , Vaccination Trend and NPI trend (Stringency Index)
Max. Total Cases
1
29,818,930
Max. Total Deaths
1
542,359
Max. Total Deaths
1
100,000
200,000
300,000
400,000
542,359
6 unknown
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