WCOVID-19 WORLD DATA ANALYSIS

By

ETHAN DEXTER BARD

BACHELOR OF SCIENCE, DATA ANALYTICS

SPRING 2022

A Project submitted in partial fulfillment of the requirements for the degree of

Master of Science, Data Science

Florida Polytechnic University

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# **Abstract**

The following report is an analysis of time-series data that aims to provide a framework for identifying countries struggling with COVID-19 and generate a model fit to forecast various relevant measures such as cases, deaths, and vaccination rates. Using COVID-19 variant data provided by GISAID and measurement data provided by Our World in Data, analytical methods such as exploratory analysis, hierarchical clustering, and time-series modeling and forecasting are performed. The significance of the emergence novel SARS-COV-2 variants are demonstrated to highlight the importance of being able to forecast important measures related to the COVID-19 pandemic. Hierarchical clustering is performed to identify similarities in trends of new COVID-19 cases over time and narrow down a subset of key countries to model and forecast. ARIMA models are fit using the auto.arima() function in R to easily generate 30 day forecasts of COVID-19 cases, deaths, and vaccination rates. The framework provided by this analysis can easily be reproduced and expanded to model a wider variety of countries, or even model other relevant time-series data features.

# Introduction

Since the emergence of SARS-COV-2, the novel coronavirus responsible for the COVID-19 pandemic beginning in early 2020, the World Health Organization (WHO) reports that nearly 500 million cases and over 6 million deaths have been documented (Who coronavirus (COVID-19) dashboard). As the virus has made its way across the globe, a multitude of mutations and variants have occurred, some of which resulting in significant changes in the contagiousness of the virus and the severity of the illness caused. It is expected that novel viruses go through many mutations in their early lifecycles, and as such it is essential that these variants are monitored to ensure the population is as prepared as possible (Katella, 2022). Furthermore, as countries around the world implement varying levels of disease prevention it is critical to be able to model and forecast cases, hospitalizations, deaths, and other measures to anticipate if additional actions need to be taken. In the following analysis, machine learning and time-series analysis methods will be demonstrated to evaluate their ability to classify, model, and forecast COVID-19 measures across the globe.

# Literature Review

## **SARS-COV-2 Variants**

To better understand the challenges and difficulties in predicting cases of COVID-19 it is essential to discuss the effect of emerging novel mutations in the SARS-COV-2 virus. In an article by Tao et al. in 2021, a framework for understanding SARS-COV-2 variants is introduced by describing some of the most important features of SARS-COV-2 evolutions, and furthermore explaining the types of studies that will be required for the research, clinical, and public health communities to effectively manage the new threats introduced by emerging SARS-COV-2 variants (Tao et al., 2021). The article explains that emergence of SARS-COV-2 variants strongly affect the epidemiological and clinical aspects of the COVID-19 pandemic because variants can become more dangerous to the public by increasing rates of virus transmission, increasing the risk of reinfection, and reducing the protection available by currently available methods of treatment such as monoclonal antibodies and vaccinations. Additionally, these variants complicate the COVID-19 research agenda and increase the need for constant laboratory, epidemiological, and clinical research. So far, many of the variants that have been identified share specific mutations that all help to enable to virus to be able to spread and replicate even though many populations are increasing in immunity. According to Tao et al. this is due to the fact that many of the recently identified SARS-COV-2 mutations appear to antagonize the innate immune response to initial infection.

SARS-COV-2 variants are classified according to their lineage and component mutations (Tao et al., 2021). The two most commonly used naming conventions for SARS-COV-2 variants are the Phylogenetic Assignment of Named Global Outbreak (PANGO) lineage and the NextStrain systems, where the PANGO lineage is used more commonly due to its greater specificity. The format of the PANGO lineage system includes an alphabetical prefix and a suffix made from up to three numbers separated by periods which indicate the sub-lineages. An example of the PANGO lineage system is the notation for the Alpha variant which is “B.1.1.7”. Multiple variants can belong to the same lineage and are differentiated by their subsets of mutations. Primarily, variants are classified by their transmissibility, disease severity, and ability to evade humoral immunity. Tao et al. continues the article by describing some of the most prevalent variants identified at the time of the article’s writing. The ”Alpha” variant B.1.1.7, which was one of the first mutations of the SARS-COV-2 virus identified, accounted for the majority of infections in the United States and many European countries by the second quarter of 2021 (Tao et al., 2021). Compared to previous variants, many of which are not classified by PANGO, the Alpha variant was suggested to be 50% more transmissible and had an estimated 50% increased mortality. The “Beta” variant B.1.351 was first identified in South Africa between October 2020 and January 2021, where daily cases jumped from around 2,000 cases to 20,000 cases per day and subsequently spreading to the rest of the world. Again, compared to previous variants, this variant was estimated to be 50% more transmissible and be more likely to cause breakthrough cases in vaccinated individuals. The “Delta” variant B.1.617.2 originated in India along with “Kappa” B.1.617.1, both of which emerged from a common ancestor lineage. The Delta variant demonstrated unprecedented transmissibility, spreading to 54 countries and quickly became the most prevalent variant in the UK and USA. While SARS-COV-2 variants all differ in their transmission rates, disease severity, and risk of infection there is no significant evidence that suggest they respond differently to public health measures such as social distancing, personal protective equipment, or antiviral therapies. Therefore, Tao et al. claims that the most important aspect of emergent SARS-COV-2 variants is primarily their impact on vaccine efficacy.

A more recent article published on Yale Medicine by Kathy Katella, a senior clinical writer describes the features and implications of the newest and most prevalent SARS-COV-2 variant “Omicron” BA.1 and its subvariant BA.2. Katella explains that Omicron was first identified in Botswana and South Africa in late November 2021, and by December 2021 Omicron was the cause of United States cases skyrocketing to over a million (Katella, 2022). BA.2 has already completely overtaken BA.1 as the predominant variant in the United states due to its significantly more rapid transmissibility. Luckily, however, BA.2 does not appear to cause more severe disease than BA.1, and is also less severe than previous variants. Nonetheless, the CDC is currently classifying Omicron as a variant of concern in the US due to its extremely high transmissibility. At the time of this study’s writing, other variants that were being monitored including Alpha, Beta, Gamma, Epsilon, Eta, Iota, Kappa, Mu, and Zeta are no longer variants of concern because they are either no longer present in the US or are spreading slowly enough to not cause concern. Unfortunately, there is still a risk of further variants to continue to emerge due to limited access to vaccines around the world.

## **Time-Series Analysis**

To aid the process of deciding how to design research and analysis, time-series data can be analyzed via cluster analysis to distinguish countries with different COVID-19 spread patterns and results. In a novel analysis performed by Zarikas et al. in 2020, countries were clustered with respect to active cases, active cases per population, and active cases per population and per area based on Johns Hopkins epidemiological data (Zarikas et al., 2020). In that analysis they claimed that clustering can support identification of possible causes of different impacts of the pandemic in different countries which in turn aids researchers to decide how to perform extended research. It was found that taking population and surface area into consideration resulted in significant changes to the cluster outputs. Some important conclusions made during their cluster analysis include the following: First, clustering with respect to active cases alone shows that countries in shared clusters have similar time evolution of the active cases, implying they have faced similar stresses to the health system. Second, clustering with respect to active cases per population shows that countries in shared clusters have experienced similar stresses to the society and the economy. Finally, clustering with respect to active cases per population per area is helpful for deriving conclusions about the impact of the disease that spreads more easily in densely populated areas. Furthermore, it was found that countries with the most critical situations tend to be smaller countries (Zarikas et al., 2020).

While cluster analysis is helpful to classify which countries have similar disease spread patterns, it is also important to be able to accurately forecast spread and results. The ability to accurately forecast when a surge of infections will hit its peak would significantly diminish the impact of the disease and allow officials to alter policies accordingly to plan ahead for preventative steps (Papastefanopoulos et al., 2020). An analysis conducted by Papastefanopoulos et al. in 2020 explored the performance of several popular time series modeling approaches for covid outbreak detection in ten countries that had the highest number of cases as of May 4th, 2020. Using data containing the progression of the virus and population of each country, six time series approaches were implemented and compared. The time series methods included in this analysis were ARIMA, HWAAS, TBAT, Prophet, DeepAR, and N-Beats. The countries included in the analysis were USA, UK, Italy, Spain, Russia, France, Turkey, Germany, Iran, and Brazil. To assess the performance of each time series model, an out of sample forecast was generated and the root mean squared error (RMSE) was calculated and compared against the other models. In summary, while each time-series approach has their own distinct positives and negatives, it was found that there was no “one size fits all” approach when it comes to predicting active cases for different countries; however, the ARIMA and TBAT approaches demonstrated superior performance in seven out of ten countries and achieved second best results in another two. Table 1 below presents the resulting RMSE of each time-series approach for each country. It is difficult to identify the specific reasons that certain algorithms perform better than others in one country but not in others, but the authors present a few suggestions that could provide some insight including country specific climate and geographical characteristics, population-related attributes such as population density, discrepancies in testing and measuring procedures and therefore data collection, and diversity in terms of quarantine and other social distancing measures (Papastefanopoulos et al., 2020).

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **US** | **Spain** | **Italy** | **UK** | **France** | **Germany** | **Russia** | **Turkey** | **Brazil** | **Iran** |
| **ARIMA** | **0.007** | 0.080 | **0.006** | 0.005 | 0.061 | 0.006 | **0.002** | 0.004 | 0.004 | 0.003 |
| Prophet | 0.014 | 0.065 | 0.019 | 0.008 | 0.044 | 0.037 | 0.015 | 0.045 | 0.009 | 0.016 |
| HWAAS | 0.173 | 0.031 | 0.007 | 0.004 | 0.011 | 0.005 | 0.002 | **0.001** | 0.006 | 0.001 |
| NBEATS | 0.037 | 0.050 | 0.009 | 0.038 | **0.004** | 0.013 | 0.027 | 0.018 | 0.011 | 0.004 |
| Gluonts | 0.045 | 0.109 | 0.044 | 0.046 | 0.011 | 0.058 | 0.034 | 0.094 | **0.003** | 0.002 |
| **TBAT** | 0.010 | **0.029** | 0.006 | **0.004** | 0.007 | **0.003** | 0.002 | 0.002 | 0.006 | **0.000** |

Table 1: RMSE Results of Time-Series Model Approaches by Country

The Auto Regressive Integrated Moving Average (ARIMA) model was originally designed for economic application and provides a high level of interpretability because the relationship between the independent variables and dependent variables are easily understood and simple to explain. The ARIMA model assumes a linear correlation between the time-series values and attempts to exploit these linear dependencies in observations to extract patterns, while removing high frequency noise from the data (Papastefanopoulos et al., 2020). A significant advantage to the ARIMA method is that models can be performed in an automated way to maximize prediction accuracy. For these reasons, the ARIMA method will be the time-series method of choice for the analysis conducted in this report. Additional details regarding the other mentioned time-series methods are described in the report by Papastefanapoulos et al.

# Data

The data collected for this analysis consists of two time-series datasets representing international measurements of several features related to COVID-19 and are compiled in weekly and daily intervals. The primary dataset includes daily measurements of features such as number of cases, hospitalizations, deaths, and vaccinations. Each of the listed measurements are provided in multiple formats including raw daily counts, cumulative totals, smoothed daily/weekly counts, and smoothed daily/weekly counts per hundred thousand or per million. The data includes records ranging from as early as January 1st, 2020 and is regularly updated with current observations. These records are compiled and provided by the team at Our World in Data. Our World in Data (OWID) is an organization of researchers, data scientists, and engineers whose goal is to “publish the research and data to make progress against the world’s largest problems” (Roser). OWID primarily brings data together from four types of sources including specialized institutes, research articles, international institutions or statistical agencies, and official data from government sources (Roser).

The secondary dataset utilized in this analysis includes weekly international measurements of COVID-19 sequencing results. The features provided in this dataset include the total number of sequences analyzed, total number of sequences classified per variant, and the proportion of sequences classified per variant as a percentage of the total number of sequences. The data does not directly represent the number of COVID-19 cases but provides insight as to which COVID-19 variant(s) are the most prevalent internationally at a given point in time. These records are compiled and provided by GISAID ranging from December 29th, 2019, to the current day. GISAID is a global science initiative and primary source established in 2008 that provides open access to genomic data of influenza viruses and the coronavirus responsible for COVID-19. This includes “genetic sequence and related clinical and epidemiological data associated with human viruses, as well as species-specific data associated with avian and other animal viruses, to help researchers understand how viruses evolve and spread during epidemics and pandemics” (Mission).

# Methods

**Exploratory Data Analysis**

An initial exploration of the datasets were conducted to examine the structure, variance, and amount of available data for analysis. Summary statistics were compiled and presented in tables B-1 and B-2. Additionally, the total percent of missing records grouped by location were compiled to see if any locations lacked a significant volume of records. Fortunately, the dataset is relatively up-to-date and most countries have a sufficient amount of data for evaluation in terms of COVID-19 cases, however some countries are not as up-to-date with their variant sequencing records, so evaluations regarding COVID-19 variants may be unreliable in those cases.

To begin the exploratory analysis, data concerning the United States were the initial focus for visualization in an attempt to identify any patterns or relationships between the proportion of COVID-19 variants sequenced and various other measures such as new cases, deaths, hospitalizations, and vaccinations. Figure 1 below depicts the proportion of covid variants against the number of new COVID-19 cases per million in the USA. Some significant patterns can be seen here which reflect the general narrative surrounding the COVID-19 Variants in the US such as the first dip in cases as vaccines were made available to the public, the second wave as the Delta variant increased in prevalence, and the third extremely large wave of cases as Omicron increased in prevalence. It should be noted that there is a delay between the measures and variant proportions due to the fact that it takes time for variant sequencing to be completed, and will often be behind by some time depending on how quickly each country is able to complete and report their sequencing. By comparing the trends seen in Figure 1 against the trends seen in Figures A-1 through A-4 one can see how the vaccines initially seemed to cause a strong decrease in cases, deaths, and hospitalizations, but even though vaccinations increased over time, the introduction of the Alpha, Delta, and Omicron variants all came with increases in cases, hospitalizations, and deaths. Fortunately, the number of new deaths never reached the same peak that was reached in early 2021 as vaccines were first becoming available to the public, suggesting that the vaccines did play a role in reducing the number of deaths.

Chart

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Figure 1: Proportion of Covid Variants vs. New Cases Per Million – USA

To further examine the relationship between covid cases and variant on a broader scale, the SF R package was used to visualize these features on a global spatial map. By first examining the most prevalent COVID-19 variants by country in Figure 2 below, it can be seen that virtually every single country on the map with available data currently reports that Omicron (B.1.1.529) is their most prevalent variant. Upon further examination, the countries which report alternative variants to be the most prevalent are typically behind in their sequencing records ranging from several weeks to several months behind. One significant exception that will be further examined in the following sections of this analysis is Austria, which has up-to-date records indicating that an unidentified variant is quickly rising in prevalence. Table B-4 presents the most recent date available for variant sequencing along with the most prevalent variant per country.

Map

Description automatically generated

Figure 2: Most Prevalent Covid Variant by Country

Figure 3 below and Table B-5 present the most recently reported number of new cases by country. In this view South Korea, France, and Germany stand out as having the highest number of new cases, each reporting approximately twice as many cases as the next country on the list, Italy. These countries will be noted for further examination. Furthermore, a similar visualization is presented in Figure A-11 depicting the number of new cases per million, which allows countries with smaller populations to potentially stand out.

Map

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Figure 3: New Cases by Country

## **Hierarchical Cluster Analysis**

To better understand which countries experienced similar patterns of cases hierarchical cluster analysis is performed. Hierarchical clustering of COVID-19 epidemiological data is valuable because it can help objectively distinguish countries that have different COVID-19 spread and results (Zarikas et al., 2020). For this analysis, hierarchical clustering was conducted using base R to calculate the Euclidean distance between COVID-19 case vectors and then apply Ward’s method to fit each Country to a cluster. The clusters in general appear to be defined based on the average amount of new cases observed over time and the severity of the most recent spike in increased new cases caused by the Omicron variant. With the help of the classifications identified by the clustering process, several countries are chosen to be the focus for the remainder of the analysis. Countries were chosen for analysis based on their cluster assignments and current severity of cases as identified in the EDA.

## **Time Series Analysis**

The objective of this analysis is to determine the future trend of various COVID-19 measures of key countries such as cases, deaths, and vaccinations. The countries selected for further analysis via Time Series modeling and forecasting include the United States, India, Austria, France, Germany, Italy, South Korea, China, Thailand, and Vietnam. Due to the fact that each country will have their own unique pattern of cases, deaths, and vaccination rates forecasting models will need to be tailored to each individual country and it will be impossible to apply a one-size-fits-all model. For these reasons, plus the conclusions made by Papastefanopoulos et al. in 2020 as discussed in the literature review, the Auto Regressive Integrated Moving Average (ARIMA) method was selected to be the time-series method used in this analysis for forecasting. The ARIMA method is well-suited to this problem because the method is easy to implement programmatically, generally performs well even with limited data, and was among the top performing methods in the analysis conducted by Papastefanopoulos et al (Papastefanopoulos et al., 2020). To implement the ARIMA method, R packages tsibble, forecast, and tseries were used. According to the documentation, the auto.arima() function from the forecast package returns the best ARIMA model hyperparameters P, D, and Q according to either AIC, AICc or BIC value. “P” is the number of autorgressive terms, “D” is the number of nonseasonal differences needed for stationarity, and “Q” is the number of lagged forecast errors in the prediction equation (*Introduction to ARIMA: nonseasonal models*) . For this analysis the best combination of P, D, and Q was selected based on the AIC, or Akaike Information Criterion, which is an estimator of out-of-sample prediction error and is used to determine the relative quality of statistical models (Zajic, 2019). Using the model fit as determined by the auto.arima() function, a forecast of new COVID-19 cases, deaths, and vaccinations for the next 30 days is generated along with a 95% confidence interval range for each country modeled.

# Results

## **Hierarchical Cluster Analysis**

Cutting the hierarchy to create 5 clusters resulted in clusters one through five containing 178, 14, 22, 1, and 1 countries respectively. A generalized examination of the clusters shows that most of the countries in clusters 1 and 2 have experienced relatively fewer new cases of COVID-19 over time but are seeing very high spikes in cases in the past few months, while the countries in clusters 3, 4, and 5 have generally reported a relatively higher amount of COVID-19 cases over time and are also seeing a high spike in recent cases. Figures 4, 5, and 6 presents the world map with countries colored by their cluster assignment, and Table x in Appendix B lists each country in order of most recent new cases along with their cluster assignment and currently most prevalent variant. Additionally, figures 7-10 below present the timeline and trend of new cases for each country included in the cluster assignments with the exception of cluster 1 countries as there are too many to plot in a visible format. Countries that are referred to as the “NA” cluster are countries that either did not have any COVID-19 case records available and therefore were not assigned to any cluster.

Map

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Figure 4: Countries Clustered by Cases Over Time

Map

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Figure 5: European Countries Clustered by Cases Over Time

Map

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Figure 6: Asian Countries Clustered By Cases Over Time

A picture containing diagram

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Figure 7: New Cases Smoothed, Countries Assigned to Cluster 2

Chart

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Figure 8: New Cases Smoothed, Countries Assigned to Cluster 3

Chart, line chart

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Figure 9: New Cases Smoothed of India, Only Assignment In Cluster 4

Chart, line chart

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Figure 10: New Cases Smoothed of The United States, Only Assignment in Cluster 5

**Time Series Analysis**

Using the auto.arima() function in R, the best model parameters P, D, and Q are identified based on the best resulting AIC. Tables 2, 3, and 4 below present the resulting evaluation metrics of the models produced. The overall accuracy of the model is measured by the root mean squared error (RMSE) which varied significantly depending on the country and measure evaluated. Additionally, the forecasts for the United States are presented below in figures 11 through 13, and the remaining forecast visualizations for the other selected countries can be found in Appendix A. The models forecasting new deaths appear to have performed the best in general due to having overall lower RMSE values. For new cases the USA, Germany, and France had had the highest RMSE, suggesting that the predictions may not be as accurate as the predictions made for other countries. The models forecasting new vaccinations had significantly higher RMSE values across the board. Of the chosen countries modeled here, only the USA, Germany, and China still appear to have a predicted forecast of cases continuing to increase in the next 30 days. Fortunately, all chosen countries appear to have a predicted forecast that deaths will continue to decrease in the next 30 days, and similarly all countries show a predicted forecast that vaccinations are decreasing as well.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **New Cases Smoothed** | | | | |
| **Country** | **ARIMA Parameters Selected** | **RMSE** | **AIC** | **BIC** |
| USA | ARIMA(3,1,4) | 6679.878 | 16627.02 | 16664.62 |
| India | ARIMA(2,1,2) | 918.9514 | 13284.38 | 13307.83 |
| Austria | ARIMA(3,1,2) | 511.0791 | 11941.56 | 11969.51 |
| France | ARIMA(0,1,2) | 4243.799 | 15519.13 | 15537.93 |
| Germany | ARIMA(1,1,3) | 3506.469 | 15478.13 | 15506.19 |
| Italy | ARIMA(1,1,5) | 1156.712 | 13624.32 | 13657.14 |
| South Korea | ARIMA(5,1,0) | 2282.981 | 14877.66 | 14905.85 |
| Vietnam | ARIMA(5,1,3) | 2599.927 | 15095.63 | 15137.93 |
| China | ARIMA(4,2,0) | 251.8862 | 11189.92 | 11213.41 |
| Thailand | ARIMA(3,1,2) | 529.6249 | 12490.8 | 12523.7 |

Table 2: Evaluation Metrics For New Cases Smoothed Models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **New Deaths Smoothed** | | | | |
| **Country** | **ARIMA Parameters Selected** | **RMSE** | **AIC** | **BIC** |
| USA | ARIMA(3,1,3) | 53.42787 | 8383.43 | 8416 |
| India | ARIMA(4,1,0) | 60.03619 | 8416.17 | 8439.36 |
| Austria | ARIMA(3,1,3) | 1.875135 | 3117.03 | 3154.13 |
| France | ARIMA(5,1,0) | 17.26007 | 6685.28 | 6713.3 |
| Germany | ARIMA(3,1,4) | 9.662358 | 5648.9 | 5686.03 |
| Italy | ARIMA(4,1,0) | 7.48404 | 5380.3 | 5403.61 |
| South Korea | ARIMA(1,1,2) | 2.620837 | 3745.55 | 3764.21 |
| Vietnam | ARIMA(2,1,1) | 9.721073 | 4592.07 | 4614.23 |
| China | ARIMA(0,1,0) | 9.416997 | 5942.57 | 5947.27 |
| Thailand | ARIMA(2,1,4) | 2.467826 | 3606.76 | 3639.32 |

Table 3: Evaluation Metrics for New Deaths Smoothed Models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **New Vaccinations Smoothed** | | | | |
| **Country** | **ARIMA Parameters Selected** | **RMSE** | **AIC** | **BIC** |
| USA | ARIMA(3,2,3) | 30995.25 | 11520.27 | 11549.62 |
| India | ARIMA(1,1,2) | 405639.9 | 13137.55 | 13154.06 |
| Austria | ARIMA(1,1,0) | 683.1586 | 7332.58 | 7340.85 |
| France | ARIMA(1,1,0) | 10990.78 | 10214.58 | 10222.91 |
| Germany | ARIMA(5,1,2) | 13811.06 | 10467.2 | 10500.54 |
| Italy | ARIMA(3,2,3) | 7705.306 | 9891.11 | 9920.26 |
| South Korea | ARIMA(2,1,5) | 22381.55 | 9534.2 | 9566.45 |
| China | ARIMA(1,1,0) | 213859 | 13369.53 | 13377.91 |
| Thailand | ARIMA(2,1,3) | 22401.21 | 9506.22 | 9530.39 |

Table 4: Evaluation Metrics for New Vaccinations Smoothed Models

Chart, line chart

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Figure 11: USA 30 Day Forecast of New Cases

Chart, line chart

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Figure 12: 30 Day Forecast of New Deaths

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Figure 13: 30 Day Forecast of New Vaccinations

# Conclusions

The objective of this analysis was to utilize data science and machine learning techniques including exploratory analysis, hierarchical clustering, and time series modeling to provide a framework for identifying countries that may be on the verge of experiencing increased rates of COVID-19. By visually exploring the data it was found that virtually all countries with current data are still reporting that the Omicron COVID-19 variant is the most prevalent in terms of sequencing. Additionally, several key countries were identified to have been recently reporting significantly higher numbers of new COVID-19 cases. Hierarchical clustering analysis was performed to see if the identified countries shared similar patterns in terms of new cases over time, and it was found that several of the identified countries were assigned to Cluster 2, which included many other countries that appeared to have recently experienced an extremely high spike in cases. Finally, ARIMA models were fitted and evaluated to forecast the next 30 days of new cases, deaths, and vaccinations in each of the chosen countries. All of the chosen countries are forecasted to see a reduction in deaths and new vaccinations over the next 30 days, and are also forecasted to see a reduction in cases with the exception of the United States and Germany. The forecasts for China suggest that they will see an increase in cases, but the data for China is significantly less reliable than the other countries data and may not be reflective of real world values. The evaluation metrics of the generated models suggest that while the predictions are expected to be better than a naive forecast, there is much improvement that could be made by utilizing more sophisticated modeling or deep learning techniques. In conclusion, the results presented in this analysis seem to provide a basic yet utilizable framework for easily evaluate worldwide trends of COVID-19 data and potentially identify a crisis before one is to occur.

# Appendix A – Figures

Chart

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Figure A- 1: Proportion of COVID Variants vs New Cases Per Million In the United States

Diagram

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Figure A- 2: Proportion of COVID Variants vs People Fully Vaccinated in the United States

Diagram

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Figure A- 3: Proportion of COVID Variants vs Hospitalizations Per Million in the United States

Diagram

Description automatically generated with medium confidence

Figure A- 4: Proportion of COVID Variants vs New Deaths Per Million In the United States

Diagram, map

Description automatically generated with medium confidence

Figure A- 5: Most Prevalent COVID Variant By Country

Map

Description automatically generated

Figure A- 6: Most Prevalent COVID Variant by Country - Europe View

Chart

Description automatically generated with medium confidence

Figure A- 7: Most Prevalent COVID Variant by Country - Asia View

Map

Description automatically generated

Figure A- 8: New Cases By Country

Map

Description automatically generated

Figure A- 9: New Cases By Country - Europe View

Map

Description automatically generated

Figure A- 10: New Cases By Country - Asia View

Map

Description automatically generated

Figure A- 11: New Cases Per Million By Country

Map

Description automatically generated

Figure A- 12: New Cases Per Million By Country - Europe View

Map

Description automatically generated

Figure A- 13: New Cases Per Million By Country - Asia View

Chart, histogram

Description automatically generated

Figure A- 14: New Cases By Cluster

Map

Description automatically generated

Figure A- 15: Countries Clustered By Cases Over Time

Chart, line chart

Description automatically generated

Figure A- 16: India 30 Day Forecast of New Cases

Chart, line chart

Description automatically generated

Figure A- 17: India 30 Day Forecast of New Deaths

Chart

Description automatically generated

Figure A- 18: India 30 Day Forecast of New Vaccinations

Chart, line chart

Description automatically generated

Figure A- 19: Austria 30 Day Forecast of New Cases

A picture containing text, map, indoor

Description automatically generated

Figure A- 20: Austria 30 Day Forecast of New Deaths

Chart, line chart

Description automatically generated

Figure A- 21: Austria 30 Day Forecast of New Vaccinations

Chart

Description automatically generated

Figure A- 22: France 30 Day Forecast of New Cases

Chart

Description automatically generated

Figure A- 23: France 30 Day Forecast of New Deaths

Chart, line chart

Description automatically generated

Figure A- 24: France 30 Day Forecast of New Vaccinations

A picture containing chart

Description automatically generated

Figure A- 25: Germany 30 Day Forecast of New Cases

Chart, line chart

Description automatically generated

Figure A- 26: Germany 30 Day Forecast of New Deaths

Chart, line chart

Description automatically generated

Figure A- 27: Germany 30 Day Forecast of New Vaccinations

Chart, line chart

Description automatically generated

Figure A- 28: Italy 30 Day Forecast of New Cases

Chart

Description automatically generated

Figure A- 29: Italy 30 Day Forecast of New Deaths

Chart, line chart

Description automatically generated

Figure A- 30: Italy 30 Day Forecast of New Vacciations

Chart, scatter chart

Description automatically generated

Figure A- 31: South Korea 30 Day Forecast of New Cases

Chart

Description automatically generated with medium confidence

Figure A- 32: South Korea 30 Day Forecast of New Deaths

A picture containing text, indoor

Description automatically generated

Figure A- 33: South Korea 30 Day Forecast of New Vaccinations

Chart, line chart

Description automatically generated

Figure A- 34: Vietnam 30 Day Forecast of New Cases

Chart, line chart

Description automatically generated

Figure A- 35: Vietnam 30 Day Forecast of New Deaths

Chart

Description automatically generated

Figure A- 36: China 30 Day Forecast of New Cases

Chart

Description automatically generated

Figure A- 37: China 30 Day Forecast of New Vaccinations

Chart, line chart

Description automatically generated

Figure A- 38: Thailand 30 Day Forecast of New Cases

Chart

Description automatically generated

Figure A- 39: Thailand 30 Day Forecast of New Deaths

Chart

Description automatically generated

Figure A- 40: Thailand 30 Day Forecast of New Vaccinations

# Appendix B – Tables

Table B- 1: R Session Info

|  |
| --- |
| R version 4.1.3 (2022-03-10) |
| Platform: x86\_64-w64-mingw32/x64 (64-bit) |
| Running under: Windows 10 x64 (build 19042) |

Table B- 2: Summary Statistics of Our World in Data COVID-19 Dataset

| Summary Statistics | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **N** | **Mean** | **Std. Dev.** | **Min** | **Pctl. 25** | **Pctl. 75** | **Max** |
| total\_cases | 173553 | 2916536.518 | 18152934.019 | 1 | 2362 | 340498 | 505971634 |
| new\_cases | 173381 | 12421.008 | 88603.946 | 0 | 1 | 1069 | 4089061 |
| new\_cases\_smoothed | 172212 | 12452.367 | 87039.752 | 0 | 6.857 | 1171.286 | 3437004.571 |
| total\_deaths | 155364 | 61331.199 | 320609.625 | 1 | 87 | 7947.25 | 6203317 |
| new\_deaths | 155377 | 165.513 | 812.508 | 0 | 0 | 19 | 18144 |
| new\_deaths\_smoothed | 154230 | 166.518 | 795.689 | 0 | 0.143 | 20.714 | 14783.286 |
| total\_cases\_per\_million | 172750 | 35428.719 | 65307.118 | 0.001 | 690.327 | 44215.87 | 706541.904 |
| new\_cases\_per\_million | 172578 | 181.795 | 749.021 | 0 | 0.018 | 103.356 | 51427.491 |
| new\_cases\_smoothed\_per\_million | 171414 | 181.991 | 577.205 | 0 | 1.584 | 126.518 | 16052.608 |
| total\_deaths\_per\_million | 154574 | 549.88 | 831.855 | 0 | 20.386 | 787.23 | 6375.292 |
| new\_deaths\_per\_million | 154587 | 1.646 | 5.088 | 0 | 0 | 1.33 | 453.772 |
| new\_deaths\_smoothed\_per\_million | 153445 | 1.648 | 3.558 | 0 | 0.015 | 1.744 | 144.167 |
| reproduction\_rate | 134218 | 0.985 | 0.367 | -0.03 | 0.79 | 1.17 | 6.15 |
| icu\_patients | 24707 | 894.297 | 2617.751 | 0 | 32 | 612 | 28891 |
| icu\_patients\_per\_million | 24707 | 24.154 | 27.53 | 0 | 4.645 | 34.719 | 177.282 |
| hosp\_patients | 25429 | 4276.906 | 11530.956 | 0 | 144 | 2979 | 154540 |
| hosp\_patients\_per\_million | 25429 | 170.683 | 207.032 | 0 | 29.432 | 232.211 | 1544.082 |
| weekly\_icu\_admissions | 5851 | 465.74 | 622.019 | 0 | 50 | 660 | 4838 |
| weekly\_icu\_admissions\_per\_million | 5851 | 15.087 | 16.16 | 0 | 4.09 | 19.924 | 221.212 |
| weekly\_hosp\_admissions | 11659 | 5860.714 | 14309.719 | 0 | 358.5 | 5382.5 | 153995 |
| weekly\_hosp\_admissions\_per\_million | 11659 | 104.847 | 106.026 | 0 | 25.738 | 143.848 | 645.808 |
| total\_tests | 74807 | 18573336.129 | 69402146.85 | 0 | 333057 | 9197081 | 860024452 |
| new\_tests | 72181 | 67402.776 | 251182.926 | 1 | 2174 | 36668 | 35855632 |
| total\_tests\_per\_thousand | 74807 | 822.944 | 2023.135 | 0 | 39.761 | 793.556 | 32925.9 |
| new\_tests\_per\_thousand | 72181 | 3.263 | 9.071 | 0 | 0.27 | 2.918 | 534.013 |
| new\_tests\_smoothed | 93746 | 58579.467 | 190794.359 | 0 | 1759 | 33543 | 5471529 |
| new\_tests\_smoothed\_per\_thousand | 93746 | 2.887 | 7.552 | 0 | 0.227 | 2.638 | 147.603 |
| positive\_rate | 87029 | 0.099 | 0.115 | 0 | 0.018 | 0.14 | 1 |
| tests\_per\_case | 86084 | 148.057 | 2185.618 | 1 | 7.1 | 51.7 | 199914.9 |
| tests\_units | 96427 |  |  |  |  |  |  |
| … people tested | 15044 | 15.6% |  |  |  |  |  |
| … samples tested | 8651 | 9% |  |  |  |  |  |
| … tests performed | 71957 | 74.6% |  |  |  |  |  |
| … units unclear | 775 | 0.8% |  |  |  |  |  |
| total\_vaccinations | 48873 | 199312376.224 | 879906770.194 | 0 | 711323 | 35306926 | 11483130394 |
| people\_vaccinated | 46493 | 99366188.129 | 437884323.324 | 0 | 434531 | 20129827 | 5119773248 |
| people\_fully\_vaccinated | 43940 | 80626001.613 | 370780242.354 | 1 | 326212.5 | 16421770.5 | 4625782468 |
| total\_boosters | 21534 | 28032184.057 | 130273830.828 | 1 | 6141.5 | 5759002.75 | 1768718439 |
| new\_vaccinations | 40171 | 1158880.304 | 4281393.527 | 0 | 6130.5 | 280306 | 54507275 |
| new\_vaccinations\_smoothed | 94244 | 496853.197 | 2701449.363 | 0 | 957 | 62289 | 43545863 |
| total\_vaccinations\_per\_hundred | 48873 | 79.843 | 68.566 | 0 | 14.65 | 132.92 | 354.93 |
| people\_vaccinated\_per\_hundred | 46493 | 40.308 | 29.474 | 0 | 10.22 | 67.24 | 124.87 |
| people\_fully\_vaccinated\_per\_hundred | 43940 | 35.026 | 28.457 | 0 | 6.22 | 61.353 | 122.88 |
| total\_boosters\_per\_hundred | 21534 | 15.512 | 19.678 | 0 | 0.03 | 28.21 | 107.17 |
| new\_vaccinations\_smoothed\_per\_million | 94244 | 3153.91 | 3887.02 | 0 | 602 | 4460 | 117497 |
| new\_people\_vaccinated\_smoothed | 93274 | 196666.025 | 1116090.977 | 0 | 355 | 24163.75 | 21367597 |
| new\_people\_vaccinated\_smoothed\_per\_hundred | 93274 | 0.138 | 0.236 | 0 | 0.02 | 0.172 | 11.75 |
| stringency\_index | 140983 | 53.86 | 20.497 | 0 | 39.81 | 69.91 | 100 |
| population | 179173 | 143969610.314 | 697315633.583 | 47 | 896005 | 32776195 | 7874965730 |
| population\_density | 160641 | 459.519 | 2118.087 | 0.137 | 37.312 | 214.243 | 20546.766 |
| median\_age | 148854 | 30.652 | 9.081 | 15.1 | 22.3 | 39.1 | 48.2 |
| aged\_65\_older | 147270 | 8.837 | 6.152 | 1.144 | 3.526 | 14.312 | 27.049 |
| aged\_70\_older | 148070 | 5.575 | 4.179 | 0.526 | 2.063 | 9.167 | 18.493 |
| gdp\_per\_capita | 148507 | 19654.192 | 20584.927 | 661.24 | 4449.898 | 27936.896 | 116935.6 |
| extreme\_poverty | 97000 | 13.583 | 20.017 | 0.1 | 0.6 | 21.2 | 77.6 |
| cardiovasc\_death\_rate | 148540 | 260.357 | 120.073 | 79.37 | 168.711 | 329.942 | 724.417 |
| diabetes\_prevalence | 155799 | 8.377 | 4.689 | 0.99 | 5.35 | 10.59 | 30.53 |
| female\_smokers | 112698 | 10.648 | 10.586 | 0.1 | 1.9 | 19.3 | 44 |
| male\_smokers | 111153 | 32.787 | 13.525 | 7.7 | 21.6 | 41.3 | 78.1 |
| handwashing\_facilities | 73202 | 50.962 | 31.864 | 1.188 | 20.859 | 83.241 | 100 |
| hospital\_beds\_per\_thousand | 131755 | 3.033 | 2.451 | 0.1 | 1.3 | 4 | 13.8 |
| life\_expectancy | 168585 | 73.656 | 7.462 | 53.28 | 69.5 | 79.19 | 86.75 |
| human\_development\_index | 145116 | 0.725 | 0.15 | 0.394 | 0.602 | 0.845 | 0.957 |
| excess\_mortality\_cumulative\_absolute | 6078 | 38991.606 | 108836.199 | -37726.1 | -44.15 | 26392.25 | 1163660.5 |
| excess\_mortality\_cumulative | 6078 | 9.582 | 16.258 | -28.45 | -0.45 | 14.64 | 111.01 |
| excess\_mortality | 6078 | 15.804 | 29.521 | -95.92 | -0.56 | 22.465 | 375 |
| excess\_mortality\_cumulative\_per\_million | 6078 | 1035.395 | 1482.622 | -1826.596 | -18.981 | 1699.146 | 9573.96 |

Table B- 3: Summary Statistics of GISAID COVID-19 Variant Dataset

| Summary Statistics | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **N** | **Mean** | **Std. Dev.** | **Min** | **Pctl. 25** | **Pctl. 75** | **Max** |
| Type | 259000 |  |  |  |  |  |  |
| … AA-Subst | 84183 | 32.5% |  |  |  |  |  |
| … Clade | 38709 | 14.9% |  |  |  |  |  |
| … Lineage | 109550 | 42.3% |  |  |  |  |  |
| … Variant | 26558 | 10.3% |  |  |  |  |  |
| count | 259000 | 367.018 | 3375.668 | 1 | 2 | 35 | 97143 |
| perc\_sequences | 259000 | 29.423 | 37.9 | 0.001 | 0.452 | 59.375 | 100 |
| total | 259000 | 3890.622 | 12480.875 | 1 | 35 | 1722 | 101523 |

Table B- 4: Percent of Missing Values By Location, Our World In Data COVID-19 Dataset

| **Percent of Missing Values By Location** | |
| --- | --- |
| **location** | **Total % NA** |
| Pitcairn | 2.86 |
| Tokelau | 3.42 |
| Israel | 4.80 |
| Italy | 5.32 |
| Czechia | 5.45 |
| Denmark | 5.76 |
| Chile | 5.85 |
| France | 5.95 |
| Belgium | 6.00 |
| Palau | 6.01 |
| Switzerland | 6.13 |
| Estonia | 6.39 |
| Ireland | 6.41 |
| United Kingdom | 6.41 |
| United States | 6.56 |
| Latvia | 6.61 |
| Malaysia | 6.64 |
| Luxembourg | 6.72 |
| Canada | 6.80 |
| Spain | 6.85 |
| Norway | 6.99 |
| Portugal | 7.02 |
| Malta | 7.12 |
| Slovenia | 7.13 |
| Kiribati | 7.14 |
| Bulgaria | 7.48 |
| Lithuania | 7.48 |
| Australia | 7.51 |
| South Korea | 7.74 |
| Netherlands | 7.88 |
| Slovakia | 8.03 |
| Cyprus | 8.04 |
| Ecuador | 8.06 |
| Bolivia | 8.19 |
| Hungary | 8.24 |
| Serbia | 8.24 |
| Tonga | 8.25 |
| Turkey | 8.25 |
| Uruguay | 8.31 |
| Greece | 8.33 |
| Croatia | 8.43 |
| Zimbabwe | 8.43 |
| Niue | 8.51 |
| Argentina | 8.54 |
| Austria | 8.80 |
| India | 8.93 |
| Colombia | 8.94 |
| South Africa | 8.95 |
| Romania | 9.02 |
| Bangladesh | 9.09 |
| Paraguay | 9.14 |
| Dominican Republic | 9.19 |
| Germany | 9.29 |
| Thailand | 9.30 |
| Peru | 9.33 |
| Zambia | 9.36 |
| Mexico | 9.49 |
| Costa Rica | 9.54 |
| Sweden | 9.55 |
| Finland | 9.57 |
| Cook Islands | 9.61 |
| Poland | 9.62 |
| Saudi Arabia | 9.62 |
| Ethiopia | 9.64 |
| Turkmenistan | 9.66 |
| El Salvador | 9.67 |
| Iceland | 9.71 |
| Sint Maarten (Dutch part) | 9.72 |
| Albania | 9.72 |
| Sri Lanka | 9.75 |
| Pakistan | 9.78 |
| Panama | 9.81 |
| Ukraine | 9.83 |
| Bahrain | 9.91 |
| Guatemala | 9.91 |
| New Zealand | 9.92 |
| Russia | 9.92 |
| Japan | 9.97 |
| Malawi | 9.99 |
| Myanmar | 9.99 |
| Togo | 10.07 |
| Tuvalu | 10.07 |
| Jamaica | 10.09 |
| Kazakhstan | 10.14 |
| Indonesia | 10.18 |
| Nauru | 10.20 |
| Maldives | 10.21 |
| Uganda | 10.21 |
| Vanuatu | 10.22 |
| Mozambique | 10.22 |
| Nepal | 10.22 |
| Senegal | 10.23 |
| Kenya | 10.24 |
| United Arab Emirates | 10.32 |
| Morocco | 10.35 |
| Brazil | 10.38 |
| Ghana | 10.43 |
| Philippines | 10.53 |
| Northern Cyprus | 10.55 |
| Namibia | 10.67 |
| Rwanda | 10.76 |
| Iran | 10.77 |
| Armenia | 10.96 |
| Georgia | 11.04 |
| Cote d'Ivoire | 11.07 |
| Cuba | 11.07 |
| Bosnia and Herzegovina | 11.08 |
| Moldova | 11.09 |
| Trinidad and Tobago | 11.10 |
| Tunisia | 11.16 |
| Mongolia | 11.23 |
| Azerbaijan | 11.30 |
| Kuwait | 11.41 |
| Micronesia (country) | 11.50 |
| Suriname | 11.55 |
| Iraq | 11.58 |
| Jordan | 11.64 |
| Nigeria | 11.89 |
| North Macedonia | 11.93 |
| Botswana | 11.95 |
| Belarus | 11.99 |
| Solomon Islands | 12.01 |
| Samoa | 12.09 |
| Madagascar | 12.17 |
| Bhutan | 12.22 |
| Barbados | 12.36 |
| Jersey | 12.40 |
| Qatar | 12.43 |
| Gambia | 12.53 |
| Kyrgyzstan | 12.55 |
| Mauritania | 12.55 |
| Montenegro | 12.59 |
| World | 12.62 |
| Singapore | 12.86 |
| Lesotho | 12.90 |
| Cape Verde | 12.96 |
| Palestine | 13.07 |
| Lebanon | 13.12 |
| Laos | 13.18 |
| Niger | 13.24 |
| Yemen | 13.24 |
| Fiji | 13.25 |
| Algeria | 13.26 |
| Comoros | 13.28 |
| Vietnam | 13.31 |
| Liechtenstein | 13.32 |
| Cambodia | 13.33 |
| Haiti | 13.33 |
| Democratic Republic of Congo | 13.38 |
| Belize | 13.40 |
| Tajikistan | 13.42 |
| Guyana | 13.46 |
| Bahamas | 13.52 |
| Liberia | 13.58 |
| Mali | 13.59 |
| Benin | 13.60 |
| Mauritius | 13.67 |
| Sierra Leone | 13.70 |
| Burkina Faso | 13.71 |
| South Sudan | 13.73 |
| Djibouti | 13.76 |
| Egypt | 13.77 |
| Guernsey | 13.80 |
| Tanzania | 13.83 |
| Congo | 13.96 |
| Honduras | 13.97 |
| Timor | 13.99 |
| Gabon | 14.01 |
| Oman | 14.01 |
| Eswatini | 14.02 |
| Libya | 14.03 |
| Brunei | 14.04 |
| Uzbekistan | 14.06 |
| China | 14.10 |
| Taiwan | 14.13 |
| Guinea | 14.14 |
| Hong Kong | 14.23 |
| Equatorial Guinea | 14.24 |
| Wallis and Futuna | 14.28 |
| Sao Tome and Principe | 14.33 |
| Burundi | 14.40 |
| Cameroon | 14.49 |
| Seychelles | 14.59 |
| Nicaragua | 14.61 |
| Chad | 14.65 |
| Angola | 14.78 |
| Central African Republic | 14.88 |
| Antigua and Barbuda | 14.88 |
| Sudan | 14.91 |
| Andorra | 15.11 |
| Papua New Guinea | 15.13 |
| Guinea-Bissau | 15.14 |
| Afghanistan | 15.15 |
| Venezuela | 15.38 |
| Saint Lucia | 15.43 |
| Somalia | 15.56 |
| Saint Vincent and the Grenadines | 16.02 |
| Eritrea | 16.09 |
| Aruba | 16.14 |
| Kosovo | 16.14 |
| Grenada | 16.23 |
| Curacao | 16.25 |
| Syria | 16.27 |
| Northern Mariana Islands | 17.03 |
| San Marino | 17.29 |
| Bermuda | 17.35 |
| Saint Kitts and Nevis | 17.72 |
| Dominica | 17.87 |
| Saint Helena | 17.91 |
| French Polynesia | 18.23 |
| Isle of Man | 18.26 |
| Cayman Islands | 18.32 |
| Monaco | 18.32 |
| Puerto Rico | 18.77 |
| Guam | 18.90 |
| Marshall Islands | 18.95 |
| South America | 18.95 |
| British Virgin Islands | 18.96 |
| United States Virgin Islands | 19.02 |
| Turks and Caicos Islands | 19.10 |
| New Caledonia | 19.14 |
| Gibraltar | 19.36 |
| Europe | 19.39 |
| High income | 19.39 |
| Africa | 19.46 |
| Upper middle income | 19.48 |
| European Union | 19.50 |
| Asia | 19.52 |
| Faeroe Islands | 19.52 |
| North America | 19.54 |
| Montserrat | 19.66 |
| Greenland | 19.68 |
| Low income | 19.76 |
| Oceania | 19.93 |
| Lower middle income | 19.96 |
| Macao | 20.07 |
| Bonaire Sint Eustatius and Saba | 20.33 |
| Anguilla | 20.94 |
| Saint Pierre and Miquelon | 22.31 |
| Falkland Islands | 22.43 |
| Vatican | 23.65 |
| International | 26.13 |

Table B- 5: Most Prevalent Variant By Location

| **Most Prevalent Variant by Location** | | |
| --- | --- | --- |
| **Location** | **Most Recent Date** | **Prevalent Variant** |
| Australia | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Austria | 2022-04-17 | Other |
| Belgium | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| France | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Italy | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Japan | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Poland | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Slovakia | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| United Kingdom | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| United States | 2022-04-17 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Albania | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Brazil | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Cambodia | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Canada | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Czech Republic | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Denmark | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Germany | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Hong Kong | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| India | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Indonesia | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Iran | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Liechtenstein | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Malaysia | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mexico | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Netherlands | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Norway | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Pakistan | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Singapore | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| South Africa | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Spain | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Sweden | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Switzerland | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Trinidad and Tobago | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Vietnam | 2022-04-10 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Argentina | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bonaire | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| China | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Croatia | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Curacao | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ireland | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Israel | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Lithuania | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| New Zealand | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Palau | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Peru | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Philippines | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Portugal | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Puerto Rico | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Romania | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Senegal | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Seychelles | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Sint Maarten | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Slovenia | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Solomon Islands | 2022-04-03 | VOC Delta GK (B.1.617.2+AY.\*) |
| Thailand | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ukraine | 2022-04-03 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Aruba | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bangladesh | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Botswana | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Costa Rica | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Estonia | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| French Guiana | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Guadeloupe | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Guam | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Martinique | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mauritius | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mayotte | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Reunion | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Russia | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Saint Martin | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Sri Lanka | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Taiwan | 2022-03-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bosnia and Herzegovina | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Chile | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Colombia | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ecuador | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Finland | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Georgia | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Greece | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Kuwait | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Luxembourg | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Moldova | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Myanmar | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Panama | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Tunisia | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Turkey | 2022-03-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Algeria | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bermuda | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Kenya | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Nigeria | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| South Korea | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| NA | 2022-03-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Antigua and Barbuda | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Brunei | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Jamaica | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Nepal | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Papua New Guinea | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Suriname | 2022-03-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| American Samoa | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Andorra | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Anguilla | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ghana | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ghana | 2022-02-27 | VOC Delta GK (B.1.617.2+AY.\*) |
| Kosovo | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Maldives | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Montenegro | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mozambique | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Serbia | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Syria | 2022-02-27 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Dominican Republic | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Guinea | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Guyana | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Lebanon | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Malawi | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Monaco | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Northern Mariana Islands | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| U.S. Virgin Islands | 2022-02-20 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Democratic Republic of the Congo | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Djibouti | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Guatemala | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Malta | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Morocco | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| New Caledonia | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| New Caledonia | 2022-02-13 | VOC Delta GK (B.1.617.2+AY.\*) |
| Paraguay | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Qatar | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Venezuela | 2022-02-13 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Belize | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bulgaria | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Cameroon | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Ethiopia | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| North Macedonia | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Zambia | 2022-02-06 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Benin | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Burkina Faso | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Cabo Verde | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Jordan | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Latvia | 2022-01-30 | VOC Delta GK (B.1.617.2+AY.\*) |
| Oman | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Rwanda | 2022-01-30 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Belarus | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Canary Islands | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| El Salvador | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Iraq | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Montserrat | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Saint Lucia | 2022-01-23 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Angola | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Armenia | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Azerbaijan | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bolivia | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Gambia | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Haiti | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Hungary | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mongolia | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Niger | 2022-01-16 | Other |
| Republic of the Congo | 2022-01-16 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Central African Republic | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Chad | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Dominica | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Dominica | 2022-01-09 | VOC Delta GK (B.1.617.2+AY.\*) |
| Egypt | 2022-01-09 | VOC Delta GK (B.1.617.2+AY.\*) |
| Honduras | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Saint Kitts and Nevis | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Saint Vincent and the Grenadines | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Uganda | 2022-01-09 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| British Virgin Islands | 2022-01-02 | VOC Delta GK (B.1.617.2+AY.\*) |
| Comoros | 2022-01-02 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Cote d'Ivoire | 2022-01-02 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Cuba | 2022-01-02 | Other |
| Gabon | 2022-01-02 | Other |
| Kazakhstan | 2022-01-02 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Liberia | 2022-01-02 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Namibia | 2022-01-02 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Eswatini | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| French Polynesia | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Mali | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Saudi Arabia | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Sudan | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Zimbabwe | 2021-12-26 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Barbados | 2021-12-19 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Crimea | 2021-12-19 | VOC Delta GK (B.1.617.2+AY.\*) |
| Gibraltar | 2021-12-19 | VOC Delta GK (B.1.617.2+AY.\*) |
| Grenada | 2021-12-19 | VOC Delta GK (B.1.617.2+AY.\*) |
| South Sudan | 2021-12-19 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Tanzania | 2021-12-19 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| The Bahamas | 2021-12-19 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| The Bahamas | 2021-12-19 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Equatorial Guinea | 2021-12-12 | VOC Delta GK (B.1.617.2+AY.\*) |
| Kyrgyzstan | 2021-12-12 | VOC Delta GK (B.1.617.2+AY.\*) |
| Uruguay | 2021-12-12 | VOC Delta GK (B.1.617.2+AY.\*) |
| Sierra Leone | 2021-11-28 | VOC Omicron GRA (B.1.1.529+BA.\*) |
| Bahrain | 2021-11-14 | VOC Delta GK (B.1.617.2+AY.\*) |
| Turks and Caicos Islands | 2021-11-14 | VOC Delta GK (B.1.617.2+AY.\*) |
| Saint Barthelemy | 2021-11-07 | VOC Delta GK (B.1.617.2+AY.\*) |
| Mauritania | 2021-10-24 | VOC Delta GK (B.1.617.2+AY.\*) |
| Cayman Islands | 2021-10-17 | VOC Delta GK (B.1.617.2+AY.\*) |
| Iceland | 2021-09-05 | VOC Delta GK (B.1.617.2+AY.\*) |
| Cyprus | 2021-08-29 | VOC Delta GK (B.1.617.2+AY.\*) |
| Lesotho | 2021-08-29 | VOC Delta GK (B.1.617.2+AY.\*) |
| Nicaragua | 2021-08-29 | VOC Delta GK (B.1.617.2+AY.\*) |
| Laos | 2021-08-08 | Other |
| Timor-Leste | 2021-08-08 | VOC Delta GK (B.1.617.2+AY.\*) |
| Burundi | 2021-08-01 | VOC Delta GK (B.1.617.2+AY.\*) |
| Sao Tome and Principe | 2021-08-01 | VOC Delta GK (B.1.617.2+AY.\*) |
| Togo | 2021-08-01 | VOC Delta GK (B.1.617.2+AY.\*) |
| Uzbekistan | 2021-07-25 | VOC Delta GK (B.1.617.2+AY.\*) |
| Madagascar | 2021-07-18 | VOC Beta GH/501Y.V2 (B.1.351+B.1.351.2+B.1.351.3) |
| Fiji | 2021-07-11 | VOC Delta GK (B.1.617.2+AY.\*) |
| United Arab Emirates | 2021-06-27 | VOC Delta GK (B.1.617.2+AY.\*) |
| Libya | 2021-06-13 | VOI Eta G/484K.V3 (B.1.525) |
| Afghanistan | 2021-05-30 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Faroe Islands | 2021-05-09 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Wallis and Futuna Islands | 2021-04-25 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Palestine | 2021-04-11 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Vanuatu | 2021-03-28 | Other |
| Somalia | 2021-03-07 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Guinea-Bissau | 2021-02-07 | VOC Alpha GRY (B.1.1.7+Q.\*) |
| Sint Eustatius | 2020-09-13 | Other |

Table B- 6: Most Recent Report of New Cases Per Million By Location

| **Most Recent Report of New Cases Per Million by Location** | | |
| --- | --- | --- |
| **Location** | **Most Recent Date** | **New Cases Per Million** |
| Cook Islands | 2022-04-19 | 5016.097 |
| South Korea | 2022-04-19 | 2095.516 |
| Bhutan | 2022-04-19 | 1746.744 |
| Cayman Islands | 2022-04-14 | 1718.634 |
| Australia | 2022-04-19 | 1672.647 |
| Samoa | 2022-04-19 | 1582.432 |
| New Zealand | 2022-04-19 | 1536.642 |
| France | 2022-04-19 | 1383.381 |
| Andorra | 2022-04-13 | 1265.056 |
| Bonaire Sint Eustatius and Saba | 2022-04-19 | 1188.450 |
| Seychelles | 2022-04-14 | 1146.786 |
| Gibraltar | 2022-04-14 | 1093.976 |
| Germany | 2022-04-19 | 1091.654 |
| Barbados | 2022-04-19 | 1056.627 |
| Luxembourg | 2022-04-19 | 1046.876 |
| Austria | 2022-04-19 | 960.009 |
| San Marino | 2022-04-19 | 848.490 |
| Italy | 2022-04-19 | 835.817 |
| Monaco | 2022-04-19 | 791.643 |
| Greece | 2022-04-19 | 776.373 |
| Finland | 2022-04-14 | 743.875 |
| Tonga | 2022-04-19 | 731.956 |
| Saint Pierre and Miquelon | 2022-04-19 | 693.121 |
| Cyprus | 2022-04-19 | 678.568 |
| Belgium | 2022-04-19 | 674.118 |
| Portugal | 2022-04-19 | 673.210 |
| Liechtenstein | 2022-04-19 | 638.589 |
| Malta | 2022-04-19 | 630.277 |
| Singapore | 2022-04-19 | 586.166 |
| Palau | 2022-04-19 | 534.516 |
| Slovenia | 2022-04-19 | 512.609 |
| Switzerland | 2022-04-19 | 462.870 |
| Canada | 2022-04-19 | 443.902 |
| Curacao | 2022-04-16 | 432.569 |
| Israel | 2022-04-19 | 426.588 |
| Brunei | 2022-04-19 | 421.584 |
| Vanuatu | 2022-04-19 | 392.959 |
| United Kingdom | 2022-04-19 | 390.770 |
| Mauritius | 2022-04-14 | 377.945 |
| Japan | 2022-04-19 | 356.161 |
| Lithuania | 2022-04-19 | 355.249 |
| Slovakia | 2022-04-19 | 349.431 |
| Estonia | 2022-04-19 | 336.556 |
| Thailand | 2022-04-19 | 323.584 |
| Bermuda | 2022-04-19 | 317.501 |
| Vietnam | 2022-04-19 | 314.844 |
| Ireland | 2022-04-19 | 308.311 |
| Denmark | 2022-04-19 | 294.767 |
| Latvia | 2022-04-19 | 267.666 |
| Malaysia | 2022-04-19 | 260.097 |
| Bahrain | 2022-04-19 | 254.207 |
| Iceland | 2022-04-18 | 236.680 |
| Aruba | 2022-04-19 | 207.899 |
| Netherlands | 2022-04-19 | 205.246 |
| Czechia | 2022-04-19 | 191.203 |
| Trinidad and Tobago | 2022-04-19 | 176.412 |
| Hungary | 2022-04-19 | 152.019 |
| Maldives | 2022-04-19 | 147.950 |
| Croatia | 2022-04-19 | 133.559 |
| Serbia | 2022-04-19 | 129.624 |
| Grenada | 2022-04-19 | 127.670 |
| Chile | 2022-04-19 | 124.704 |
| Montenegro | 2022-04-19 | 114.185 |
| Hong Kong | 2022-04-19 | 113.770 |
| United States | 2022-04-19 | 105.767 |
| Solomon Islands | 2022-04-14 | 87.663 |
| Norway | 2022-04-19 | 81.522 |
| Bulgaria | 2022-04-19 | 79.666 |
| Laos | 2022-04-19 | 78.269 |
| Panama | 2022-04-19 | 77.924 |
| Uruguay | 2022-04-17 | 76.488 |
| Russia | 2022-04-19 | 71.301 |
| Belarus | 2022-04-19 | 63.706 |
| Romania | 2022-04-19 | 61.033 |
| Brazil | 2022-04-19 | 60.705 |
| Sweden | 2022-04-14 | 56.467 |
| Taiwan | 2022-04-19 | 54.161 |
| North Macedonia | 2022-04-19 | 53.846 |
| Georgia | 2022-04-19 | 53.521 |
| Turkey | 2022-04-19 | 52.401 |
| Saint Lucia | 2022-04-19 | 51.131 |
| Turks and Caicos Islands | 2022-04-19 | 47.345 |
| Qatar | 2022-04-19 | 35.245 |
| Moldova | 2022-04-19 | 33.300 |
| Cuba | 2022-04-19 | 33.286 |
| Montserrat | 2022-04-19 | 28.680 |
| Argentina | 2022-04-17 | 26.272 |
| French Polynesia | 2022-04-19 | 25.787 |
| United Arab Emirates | 2022-04-19 | 24.393 |
| Belize | 2022-04-19 | 23.638 |
| Antigua and Barbuda | 2022-04-19 | 23.152 |
| South Africa | 2022-04-19 | 22.991 |
| Iran | 2022-04-19 | 22.317 |
| Poland | 2022-04-19 | 21.158 |
| Peru | 2022-04-19 | 20.007 |
| China | 2022-04-19 | 19.884 |
| Marshall Islands | 2022-04-19 | 19.170 |
| Lebanon | 2022-04-19 | 18.994 |
| Saint Kitts and Nevis | 2022-04-19 | 18.676 |
| Guatemala | 2022-04-19 | 17.879 |
| Bahamas | 2022-04-19 | 16.196 |
| Dominica | 2022-04-19 | 13.856 |
| Honduras | 2022-04-19 | 13.785 |
| Kuwait | 2022-04-19 | 13.762 |
| Ecuador | 2022-04-19 | 13.273 |
| Albania | 2022-04-19 | 13.078 |
| Namibia | 2022-04-19 | 11.540 |
| Bosnia and Herzegovina | 2022-04-19 | 11.469 |
| New Caledonia | 2022-04-19 | 11.400 |
| Eswatini | 2022-04-19 | 11.332 |
| Jamaica | 2022-04-19 | 10.522 |
| Tunisia | 2022-04-19 | 10.341 |
| Saint Vincent and the Grenadines | 2022-04-19 | 10.271 |
| Mongolia | 2022-04-19 | 10.127 |
| Kosovo | 2022-04-19 | 9.138 |
| Kiribati | 2022-04-19 | 8.238 |
| Guyana | 2022-04-19 | 7.230 |
| Palestine | 2022-04-19 | 7.084 |
| Jordan | 2022-04-19 | 6.608 |
| Zambia | 2022-04-19 | 6.312 |
| Suriname | 2022-04-19 | 6.276 |
| Mexico | 2022-04-19 | 5.931 |
| Bolivia | 2022-04-19 | 5.372 |
| Egypt | 2022-04-19 | 5.026 |
| Oman | 2022-04-19 | 4.950 |
| Cape Verde | 2022-04-19 | 4.831 |
| Paraguay | 2022-04-19 | 4.670 |
| Armenia | 2022-04-19 | 4.476 |
| Iraq | 2022-04-19 | 4.180 |
| Colombia | 2022-04-19 | 3.843 |
| Sao Tome and Principe | 2022-04-19 | 3.198 |
| Saudi Arabia | 2022-04-19 | 3.113 |
| Indonesia | 2022-04-19 | 3.056 |
| Venezuela | 2022-04-19 | 2.533 |
| Fiji | 2022-04-19 | 2.215 |
| Africa | 2022-04-19 | 2.211 |
| Dominican Republic | 2022-04-19 | 2.126 |
| Philippines | 2022-04-19 | 1.950 |
| Zimbabwe | 2022-04-19 | 1.922 |
| Sri Lanka | 2022-04-19 | 1.515 |
| Azerbaijan | 2022-04-19 | 1.425 |
| Burundi | 2022-04-19 | 1.329 |
| Morocco | 2022-04-19 | 1.270 |
| Kazakhstan | 2022-04-19 | 1.128 |
| India | 2022-04-19 | 0.982 |
| Timor | 2022-04-19 | 0.957 |
| Uzbekistan | 2022-04-19 | 0.939 |
| Cambodia | 2022-04-19 | 0.927 |
| Afghanistan | 2022-04-19 | 0.918 |
| Guinea | 2022-04-19 | 0.857 |
| Liberia | 2022-04-19 | 0.827 |
| Papua New Guinea | 2022-04-19 | 0.752 |
| South Sudan | 2022-04-19 | 0.678 |
| Myanmar | 2022-04-19 | 0.657 |
| Mali | 2022-04-19 | 0.610 |
| Libya | 2022-04-19 | 0.575 |
| Guinea-Bissau | 2022-04-19 | 0.496 |
| Comoros | 2022-04-19 | 0.482 |
| Djibouti | 2022-04-19 | 0.428 |
| Democratic Republic of Congo | 2022-04-14 | 0.425 |
| Pakistan | 2022-04-19 | 0.417 |
| Angola | 2022-04-19 | 0.392 |
| Gabon | 2022-04-19 | 0.376 |
| Haiti | 2022-04-19 | 0.359 |
| Nepal | 2022-04-19 | 0.327 |
| Low income | 2022-04-19 | 0.308 |
| Equatorial Guinea | 2022-04-19 | 0.296 |
| Niger | 2022-04-19 | 0.267 |
| Kyrgyzstan | 2022-04-19 | 0.259 |
| Syria | 2022-04-19 | 0.250 |
| Bangladesh | 2022-04-19 | 0.241 |
| Ethiopia | 2022-04-19 | 0.239 |
| Gambia | 2022-04-19 | 0.230 |
| Togo | 2022-04-19 | 0.202 |
| Ghana | 2022-04-19 | 0.194 |
| Senegal | 2022-04-19 | 0.166 |
| Mozambique | 2022-04-19 | 0.164 |
| Madagascar | 2022-04-19 | 0.161 |
| Malawi | 2022-04-19 | 0.153 |
| Chad | 2022-04-19 | 0.152 |
| Cote d'Ivoire | 2022-04-19 | 0.143 |
| Sudan | 2022-04-19 | 0.143 |
| Uganda | 2022-04-19 | 0.139 |
| Rwanda | 2022-04-19 | 0.129 |
| Kenya | 2022-04-19 | 0.122 |
| Somalia | 2022-04-19 | 0.122 |
| Mauritania | 2022-04-19 | 0.120 |
| Sierra Leone | 2022-04-19 | 0.070 |
| Algeria | 2022-04-19 | 0.051 |
| Eritrea | 2022-04-19 | 0.040 |
| Tanzania | 2022-04-19 | 0.030 |
| Nigeria | 2022-04-19 | 0.025 |
| Yemen | 2022-04-19 | 0.019 |
| Anguilla | 2022-04-19 | 0.000 |
| Benin | 2022-04-19 | 0.000 |
| Botswana | 2022-04-19 | 0.000 |
| British Virgin Islands | 2022-04-19 | 0.000 |
| Burkina Faso | 2022-04-19 | 0.000 |
| Cameroon | 2022-04-19 | 0.000 |
| Central African Republic | 2022-04-19 | 0.000 |
| Congo | 2022-04-19 | 0.000 |
| Costa Rica | 2022-04-19 | 0.000 |
| El Salvador | 2022-04-19 | 0.000 |
| Faeroe Islands | 2022-04-19 | 0.000 |
| Falkland Islands | 2022-04-19 | 0.000 |
| Greenland | 2022-04-19 | 0.000 |
| Isle of Man | 2022-04-19 | 0.000 |
| Lesotho | 2022-04-19 | 0.000 |
| Macao | 2022-04-19 | 0.000 |
| Micronesia (country) | 2022-04-19 | 0.000 |
| Nicaragua | 2022-04-19 | 0.000 |
| Saint Helena | 2022-04-19 | 0.000 |
| Spain | 2022-04-19 | 0.000 |
| Tajikistan | 2022-04-19 | 0.000 |
| Ukraine | 2022-04-19 | 0.000 |
| Vatican | 2022-04-19 | 0.000 |
| Wallis and Futuna | 2022-04-19 | 0.000 |
| Guam | NA | NA |
| Guernsey | NA | NA |
| International | NA | NA |
| Jersey | NA | NA |
| Nauru | NA | NA |
| Niue | NA | NA |
| Northern Cyprus | NA | NA |
| Northern Mariana Islands | NA | NA |
| Pitcairn | NA | NA |
| Puerto Rico | NA | NA |
| Sint Maarten (Dutch part) | NA | NA |
| Tokelau | NA | NA |
| Turkmenistan | NA | NA |
| Tuvalu | NA | NA |
| United States Virgin Islands | NA | NA |

Table B- 7: Most Recent Report of New Cases By Location

| **Most Recent Report of New Cases by Location** | | |
| --- | --- | --- |
| **Location** | **Most Recent Date** | **New Cases** |
| South Korea | 2022-04-19 | 107510.857 |
| France | 2022-04-19 | 93270.286 |
| Germany | 2022-04-19 | 91590.286 |
| Italy | 2022-04-19 | 50456.143 |
| Japan | 2022-04-19 | 44894.429 |
| Australia | 2022-04-19 | 43134.571 |
| United States | 2022-04-19 | 35211.429 |
| Vietnam | 2022-04-19 | 30907.857 |
| China | 2022-04-19 | 28717.286 |
| United Kingdom | 2022-04-19 | 26653.286 |
| Thailand | 2022-04-19 | 22635.000 |
| Canada | 2022-04-19 | 16898.429 |
| Brazil | 2022-04-19 | 12990.429 |
| Russia | 2022-04-19 | 10403.714 |
| Austria | 2022-04-19 | 8681.429 |
| Malaysia | 2022-04-19 | 8525.000 |
| Greece | 2022-04-19 | 8051.571 |
| New Zealand | 2022-04-19 | 7877.286 |
| Belgium | 2022-04-19 | 7841.571 |
| Portugal | 2022-04-19 | 6845.143 |
| Turkey | 2022-04-19 | 4456.286 |
| Finland | 2022-04-14 | 4127.286 |
| Switzerland | 2022-04-19 | 4034.143 |
| Israel | 2022-04-19 | 3963.429 |
| Netherlands | 2022-04-19 | 3524.714 |
| Singapore | 2022-04-19 | 3196.714 |
| Africa | 2022-04-19 | 3036.714 |
| Chile | 2022-04-19 | 2395.857 |
| Czechia | 2022-04-19 | 2050.571 |
| Slovakia | 2022-04-19 | 1904.143 |
| Iran | 2022-04-19 | 1897.571 |
| Denmark | 2022-04-19 | 1713.571 |
| Ireland | 2022-04-19 | 1536.286 |
| Hungary | 2022-04-19 | 1464.571 |
| South Africa | 2022-04-19 | 1380.429 |
| India | 2022-04-19 | 1368.286 |
| Bhutan | 2022-04-19 | 1362.286 |
| Taiwan | 2022-04-19 | 1292.000 |
| Argentina | 2022-04-17 | 1198.143 |
| Romania | 2022-04-19 | 1167.429 |
| Slovenia | 2022-04-19 | 1065.571 |
| Lithuania | 2022-04-19 | 955.571 |
| Serbia | 2022-04-19 | 890.714 |
| Hong Kong | 2022-04-19 | 859.286 |
| Indonesia | 2022-04-19 | 844.429 |
| Poland | 2022-04-19 | 799.714 |
| Mexico | 2022-04-19 | 772.571 |
| Peru | 2022-04-19 | 667.429 |
| Luxembourg | 2022-04-19 | 664.571 |
| Cyprus | 2022-04-19 | 608.000 |
| Belarus | 2022-04-19 | 601.571 |
| Laos | 2022-04-19 | 577.571 |
| Sweden | 2022-04-14 | 573.714 |
| Bulgaria | 2022-04-19 | 549.429 |
| Croatia | 2022-04-19 | 545.143 |
| Egypt | 2022-04-19 | 524.000 |
| Latvia | 2022-04-19 | 499.714 |
| Mauritius | 2022-04-14 | 481.286 |
| Estonia | 2022-04-19 | 446.000 |
| Norway | 2022-04-19 | 445.571 |
| Bahrain | 2022-04-19 | 444.429 |
| Cuba | 2022-04-19 | 376.714 |
| Panama | 2022-04-19 | 341.429 |
| Guatemala | 2022-04-19 | 326.286 |
| Malta | 2022-04-19 | 325.286 |
| Samoa | 2022-04-19 | 316.714 |
| Barbados | 2022-04-19 | 304.000 |
| Uruguay | 2022-04-17 | 266.571 |
| Trinidad and Tobago | 2022-04-19 | 247.571 |
| United Arab Emirates | 2022-04-19 | 243.714 |
| Ecuador | 2022-04-19 | 237.429 |
| Philippines | 2022-04-19 | 216.571 |
| Georgia | 2022-04-19 | 213.000 |
| Low income | 2022-04-19 | 204.571 |
| Colombia | 2022-04-19 | 197.000 |
| Brunei | 2022-04-19 | 186.143 |
| Iraq | 2022-04-19 | 172.143 |
| Honduras | 2022-04-19 | 138.714 |
| Moldova | 2022-04-19 | 134.000 |
| Lebanon | 2022-04-19 | 128.571 |
| Vanuatu | 2022-04-19 | 123.571 |
| Tunisia | 2022-04-19 | 123.429 |
| Zambia | 2022-04-19 | 119.429 |
| Cayman Islands | 2022-04-14 | 114.286 |
| Seychelles | 2022-04-14 | 113.429 |
| North Macedonia | 2022-04-19 | 112.143 |
| Saudi Arabia | 2022-04-19 | 110.000 |
| Qatar | 2022-04-19 | 103.286 |
| Andorra | 2022-04-13 | 97.857 |
| Pakistan | 2022-04-19 | 93.857 |
| Cook Islands | 2022-04-19 | 88.143 |
| Iceland | 2022-04-18 | 87.286 |
| Maldives | 2022-04-19 | 80.429 |
| Tonga | 2022-04-19 | 78.143 |
| Venezuela | 2022-04-19 | 72.714 |
| Montenegro | 2022-04-19 | 71.714 |
| Curacao | 2022-04-16 | 71.286 |
| Jordan | 2022-04-19 | 67.857 |
| Bolivia | 2022-04-19 | 63.571 |
| Solomon Islands | 2022-04-14 | 61.714 |
| Kuwait | 2022-04-19 | 59.571 |
| Morocco | 2022-04-19 | 47.429 |
| Bangladesh | 2022-04-19 | 40.143 |
| Democratic Republic of Congo | 2022-04-14 | 39.286 |
| Albania | 2022-04-19 | 37.571 |
| Bosnia and Herzegovina | 2022-04-19 | 37.429 |
| Palestine | 2022-04-19 | 37.000 |
| Gibraltar | 2022-04-14 | 36.857 |
| Afghanistan | 2022-04-19 | 36.571 |
| Myanmar | 2022-04-19 | 36.000 |
| Mongolia | 2022-04-19 | 33.714 |
| Paraguay | 2022-04-19 | 33.714 |
| Sri Lanka | 2022-04-19 | 32.571 |
| Uzbekistan | 2022-04-19 | 31.857 |
| Bonaire Sint Eustatius and Saba | 2022-04-19 | 31.429 |
| Jamaica | 2022-04-19 | 31.286 |
| Monaco | 2022-04-19 | 31.286 |
| Namibia | 2022-04-19 | 29.857 |
| Zimbabwe | 2022-04-19 | 29.000 |
| San Marino | 2022-04-19 | 28.857 |
| Ethiopia | 2022-04-19 | 28.143 |
| Oman | 2022-04-19 | 25.857 |
| Liechtenstein | 2022-04-19 | 24.429 |
| Dominican Republic | 2022-04-19 | 23.286 |
| Aruba | 2022-04-19 | 22.286 |
| Kazakhstan | 2022-04-19 | 21.429 |
| Bermuda | 2022-04-19 | 19.714 |
| Burundi | 2022-04-19 | 16.286 |
| Kosovo | 2022-04-19 | 16.286 |
| Cambodia | 2022-04-19 | 15.714 |
| Azerbaijan | 2022-04-19 | 14.571 |
| Grenada | 2022-04-19 | 14.429 |
| Angola | 2022-04-19 | 13.286 |
| Armenia | 2022-04-19 | 13.286 |
| Eswatini | 2022-04-19 | 13.286 |
| Mali | 2022-04-19 | 12.714 |
| Guinea | 2022-04-19 | 11.571 |
| Nepal | 2022-04-19 | 9.714 |
| Palau | 2022-04-19 | 9.714 |
| Belize | 2022-04-19 | 9.571 |
| Saint Lucia | 2022-04-19 | 9.429 |
| South Sudan | 2022-04-19 | 7.714 |
| French Polynesia | 2022-04-19 | 7.286 |
| Papua New Guinea | 2022-04-19 | 6.857 |
| Kenya | 2022-04-19 | 6.714 |
| Niger | 2022-04-19 | 6.714 |
| Uganda | 2022-04-19 | 6.571 |
| Bahamas | 2022-04-19 | 6.429 |
| Sudan | 2022-04-19 | 6.429 |
| Ghana | 2022-04-19 | 6.143 |
| Guyana | 2022-04-19 | 5.714 |
| Mozambique | 2022-04-19 | 5.286 |
| Nigeria | 2022-04-19 | 5.286 |
| Madagascar | 2022-04-19 | 4.571 |
| Syria | 2022-04-19 | 4.571 |
| Liberia | 2022-04-19 | 4.286 |
| Haiti | 2022-04-19 | 4.143 |
| Libya | 2022-04-19 | 4.000 |
| Saint Pierre and Miquelon | 2022-04-19 | 4.000 |
| Cote d'Ivoire | 2022-04-19 | 3.857 |
| Suriname | 2022-04-19 | 3.714 |
| New Caledonia | 2022-04-19 | 3.286 |
| Malawi | 2022-04-19 | 3.000 |
| Senegal | 2022-04-19 | 2.857 |
| Cape Verde | 2022-04-19 | 2.714 |
| Chad | 2022-04-19 | 2.571 |
| Algeria | 2022-04-19 | 2.286 |
| Antigua and Barbuda | 2022-04-19 | 2.286 |
| Fiji | 2022-04-19 | 2.000 |
| Somalia | 2022-04-19 | 2.000 |
| Tanzania | 2022-04-19 | 1.857 |
| Turks and Caicos Islands | 2022-04-19 | 1.857 |
| Kyrgyzstan | 2022-04-19 | 1.714 |
| Rwanda | 2022-04-19 | 1.714 |
| Togo | 2022-04-19 | 1.714 |
| Timor | 2022-04-19 | 1.286 |
| Marshall Islands | 2022-04-19 | 1.143 |
| Saint Vincent and the Grenadines | 2022-04-19 | 1.143 |
| Dominica | 2022-04-19 | 1.000 |
| Guinea-Bissau | 2022-04-19 | 1.000 |
| Kiribati | 2022-04-19 | 1.000 |
| Saint Kitts and Nevis | 2022-04-19 | 1.000 |
| Gabon | 2022-04-19 | 0.857 |
| Sao Tome and Principe | 2022-04-19 | 0.714 |
| Gambia | 2022-04-19 | 0.571 |
| Mauritania | 2022-04-19 | 0.571 |
| Sierra Leone | 2022-04-19 | 0.571 |
| Yemen | 2022-04-19 | 0.571 |
| Comoros | 2022-04-19 | 0.429 |
| Djibouti | 2022-04-19 | 0.429 |
| Equatorial Guinea | 2022-04-19 | 0.429 |
| Eritrea | 2022-04-19 | 0.143 |
| Montserrat | 2022-04-19 | 0.143 |
| Anguilla | 2022-04-19 | 0.000 |
| Benin | 2022-04-19 | 0.000 |
| Botswana | 2022-04-19 | 0.000 |
| British Virgin Islands | 2022-04-19 | 0.000 |
| Burkina Faso | 2022-04-19 | 0.000 |
| Cameroon | 2022-04-19 | 0.000 |
| Central African Republic | 2022-04-19 | 0.000 |
| Congo | 2022-04-19 | 0.000 |
| Costa Rica | 2022-04-19 | 0.000 |
| El Salvador | 2022-04-19 | 0.000 |
| Faeroe Islands | 2022-04-19 | 0.000 |
| Falkland Islands | 2022-04-19 | 0.000 |
| Greenland | 2022-04-19 | 0.000 |
| International | 2022-04-19 | 0.000 |
| Isle of Man | 2022-04-19 | 0.000 |
| Lesotho | 2022-04-19 | 0.000 |
| Macao | 2022-04-19 | 0.000 |
| Micronesia (country) | 2022-04-19 | 0.000 |
| Nicaragua | 2022-04-19 | 0.000 |
| Saint Helena | 2022-04-19 | 0.000 |
| Spain | 2022-04-19 | 0.000 |
| Tajikistan | 2022-04-19 | 0.000 |
| Ukraine | 2022-04-19 | 0.000 |
| Vatican | 2022-04-19 | 0.000 |
| Wallis and Futuna | 2022-04-19 | 0.000 |
| Guam | NA | NA |
| Guernsey | NA | NA |
| Jersey | NA | NA |
| Nauru | NA | NA |
| Niue | NA | NA |
| Northern Cyprus | NA | NA |
| Northern Mariana Islands | NA | NA |
| Pitcairn | NA | NA |
| Puerto Rico | NA | NA |
| Sint Maarten (Dutch part) | NA | NA |
| Tokelau | NA | NA |
| Turkmenistan | NA | NA |
| Tuvalu | NA | NA |
| United States Virgin Islands | NA | NA |

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