

PROJECT II REPORT: GLOBAL COVID-19 ANALYSIS & VISUALIZATION

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1 Introduction

The outbreak of the COVID-19 pandemic in late 2019 marked the beginning of an unprecedented global health crisis. The novel coronavirus (SARS-CoV-2) rapidly spread across countries and continents, severely challenging public health systems, economies, and societal structures. In response to this evolving emergency, accurate and up-to-date data became essential for governments, researchers, healthcare professionals, and the general public to make informed decisions and implement effective containment strategies.

However, the massive volume and complexity of pandemic-related data presented considerable challenges. As case numbers, death rates, and testing metrics surged globally, many stakeholders lacked the tools to efficiently analyze and interpret this rapidly changing information. Traditional tabular reports or static charts often failed to capture the multidimensional, dynamic nature of the pandemic, especially when users sought to understand temporal and geographic trends simultaneously.

To address this issue, our project aims to develop an interactive, user-friendly data visualization tool using the **Shiny** web application framework in **RStudio**. This tool is designed to help users explore the progression of COVID-19 across time and space through a set of intuitive and customizable visualizations. The primary goal is to bridge the gap between raw epidemiological data and actionable insight, enabling users—whether technical or non-technical—to observe patterns, compare regions, and understand the impact of the pandemic over time.

The core dataset used in this project is the **Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) COVID-19 time series dataset**, which spans from **January 22, 2020 to March 7, 2023**. The full dataset resources are publicly available at: <https://github.com/CSSEGISandData/COVID-19>, and you can find some attributes we loaded and used in Table 1.

Variable	Description
Date	Daily timestamps indicating when data was recorded.
Country/Region	The name of the reporting country or territory.
Province/State	Subnational administrative divisions (when applicable).
Latitude & Longitude	Geographic coordinates (latitude and longitude) for mapping.
Confirmed	Cumulative number of confirmed COVID-19 cases.
Deaths	Cumulative number of reported deaths.
Recovered	Cumulative number of recoveries (though this variable has limited availability in some countries).

Table 1: Description of Variables in the JHU COVID-19 Dataset

```

1 library(data.table)
2 library(leaflet)
3 library(shiny)
4
5 markerLegendHTML <- function(IconSet) {
6   legendHtml <- "<div style='padding: 10px;'><h4> Confirmed </h4>"
7   n <- 1
8   for (Icon in IconSet) {
9     if (Icon[["library"]] == "glyphicon") {
10      legendHtml <- paste0(
11        legendHtml,
12        "<div style='height: 45px;'>",
13        "<div class='awesome-marker awesome-marker-icon-'",
14        Icon[["markerColor"]],

```

```

15     "><i class='glyphicon glyphicon-",
16     Icon[[ "icon" ]],
17     "' style='color: ",
18     Icon[[ "iconColor" ]],
19     "></i></div>",
20     "<p>", names(IconSet)[n], "</p></div>"
21   )
22 }
23 n <- n + 1
24 }
25 paste0(legendHtml, "</div>")
26 }
27
28 popup_icons <- awesomeIconList(
29   "0" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "green"),
30   "1-100" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "
lightblue"),
31   "101-10000" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "
orange"),
32   "10001-100000" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "
red"),
33   "100001-1000000" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "
black"),
34   "1000000-" = makeAwesomeIcon(icon = "stats", library = "glyphicon", markerColor = "
black", iconColor = "darkred")
35 )
36
37 datasource <- "jhu"
38
39 if (datasource == "jhu") {
40   site_link <- paste0(
41     "https://raw.githubusercontent.com/",
42     "CSSEGISandData/COVID-19/master/csse_covid_19_data/csse_covid_19_time_series/"
43   )
44   confirmed_data <- fread(RCurl::getURL(paste0(site_link, "
time_series_covid19_confirmed_global.csv")))
45   recovered_data <- fread(RCurl::getURL(paste0(site_link, "
time_series_covid19_recovered_global.csv")))
46   death_data <- fread(RCurl::getURL(paste0(site_link, "time_series_covid19_deaths_global.
csv")))
47
48   cols <- names(recovered_data)[5:ncol(recovered_data)]
49   recovered_data[, (cols) := lapply(.SD, as.integer), .SDcols = cols]
50
51   confirmed <- melt(confirmed_data, id = 1:2, measure = 3:ncol(confirmed_data),
52     variable.name = "Date", value.name = "Num")
53   recovered <- melt(recovered_data, id = 1:4, measure = 5:ncol(recovered_data),
54     variable.name = "Date", value.name = "Num")
55   death <- melt(death_data, id = 1:4, measure = 5:ncol(death_data),
56     variable.name = "Date", value.name = "Num")
57
58   confirmed = merge(
59     confirmed,
60     recovered[, .(Province/State, Country/Region, Date, Lat, Long)],
61     by = c('Province/State', 'Country/Region', 'Date'),
62     all.x = TRUE
63   )
64
65   confirmed[, Type := "Confirmed"]
66   recovered[, Type := "Recovered"]
67   death[, Type := "Deaths"]
68
69   data <- rbindlist(list(confirmed, recovered, death), fill = TRUE)
70   data <- data[!is.na(data$Lat)]
71   data[is.na(Num), Num := 0]
72   data[, Date := lubridate::mdy(Date)]
73
74   data <- dcast(data, ... ~ Type, value.var = "Num")
75   data <- data[
76     !('Province/State' %in% c("Recovered", "Diamond Princess", "Grand Princess")) &

```

```

77 !is.na(Confirmed) & !is.na(Deaths) & Confirmed >= 0 & Deaths >= 0
78 ]
79 data[is.na(Recovered), Recovered := 0]
80
81 data[, ':= '(
82   Current = Confirmed - Deaths - Recovered,
83   DeathRate = Deaths / ifelse(Confirmed == 0, 1, Confirmed)
84 )]
85
86 setnames(data,
87   c("Country/Region", "Province/State", "Lat", "Long"),
88   c("CountryName", "RegionName", "Latitude", "Longitude")
89 )
90 }
91
92 country_data <- data[, .(
93   Confirmed = sum(Confirmed),
94   Deaths = sum(Deaths)
95 ), by = .(CountryName, Date)]
96
97 country_names <- c("World", unique(country_data[order(-Confirmed)][, CountryName]))
98
99 data[, ':= '(
100   Date = as.Date(Date),
101   icon_group = cut(
102     data$Confirmed,
103     breaks = c(-1, 0, 100, 10000, 100000, 1000000, 1e9),
104     labels = c("0", "1-100", "101-10000", "10001-100000", "100001-1000000", "1000000-")
105   ),
106   label = paste0(
107     CountryName,
108     "<br> ", RegionName,
109     "<br> #Confirmed: ", Confirmed,
110     "<br> #Deaths: ", Deaths
111   )
112 )]
```

Listing 1: Script for loading and transforming COVID-19 data

Our solution introduces several novelties:

1. **Customizability and Interactivity:** Unlike many static reports or one-size-fits-all dashboards, our Shiny application allows users to customize the data view by selecting specific countries or regions, date ranges, and metrics of interest.
2. **Time-Sensitive Comparative Analysis:** Our application supports side-by-side comparisons across regions and timeframes, helping users observe how different countries responded to the pandemic and how their trajectories varied over time.
3. **Geospatial Visualization:** Using the geographic coordinates provided in the dataset, we built map-based visualizations with tools such as `leaflet`, enabling users to observe the spatial spread of the virus.

By developing a dynamic, flexible, and insightful visualization tool grounded in a widely trusted dataset, this project contributes a novel resource for COVID-19 data analysis. It supports informed exploration for academic researchers, public health analysts, and engaged citizens alike.

2 Research Question 1: How does a nation's economic capacity influence its ability to respond to and recover from the COVID-19 pandemic across different continents?

2.1 Introduction

The interactive map visually suggests that Europe has significantly more reported COVID-19 cases than Africa, as indicated by the dense concentration of darker-colored markers.

However, this apparent disparity might be misleading. The reasons is that differences in testing capacity, reporting infrastructure, and data transparency across regions—especially underreporting in African countries.

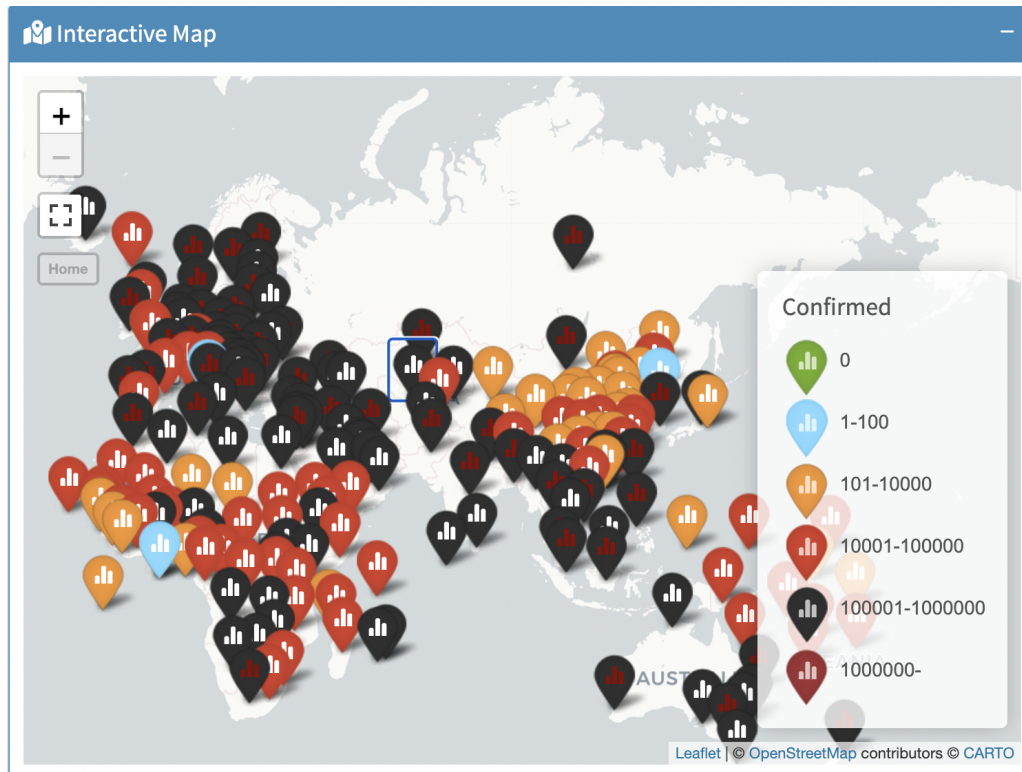


Figure 1: Interactive map showing the distribution of confirmed COVID-19 cases across countries

2.2 Approach

To address the question of whether Europe truly had more COVID-19 cases than Africa—and to better understand the relationship between a country’s economic capacity and the seriousness of COVID-19 outcomes—I expanded the analysis beyond the interactive Shiny app. The visualization alone could be misleading due to potential underreporting and differences in testing coverage. Therefore, I combined multiple datasets, including accumulated COVID-19 cases, deaths, testing numbers, and GDP per capita (2022), to gain deeper insights into global disparities in pandemic reporting and impact.

Specifically, my analysis focused on:

1. **The correlation between testing numbers and total reported cases**
2. **The correlation between GDP per capita and testing performed**
3. **The correlation between GDP per capita and COVID-19 death rates**

By examining these relationships, we aimed to reveal how economic factors may influence both the detection and the outcomes of the pandemic across different regions.

The full implementation can be accessed in `app.R` file and **Research Question 1** folder available on our GitHub repository (Section 4).

2.3 Analysis & Discussion

2.3.1 The correlation between testing numbers and total reported cases

In Figure 2, we can observe that the correlation between testing rates and reported COVID-19 case rates is moderately strong (correlation = 0.577). This suggests that countries conducting more tests tend to report more cases, indicating that higher testing capacity likely leads to more accurate and comprehensive case detection.

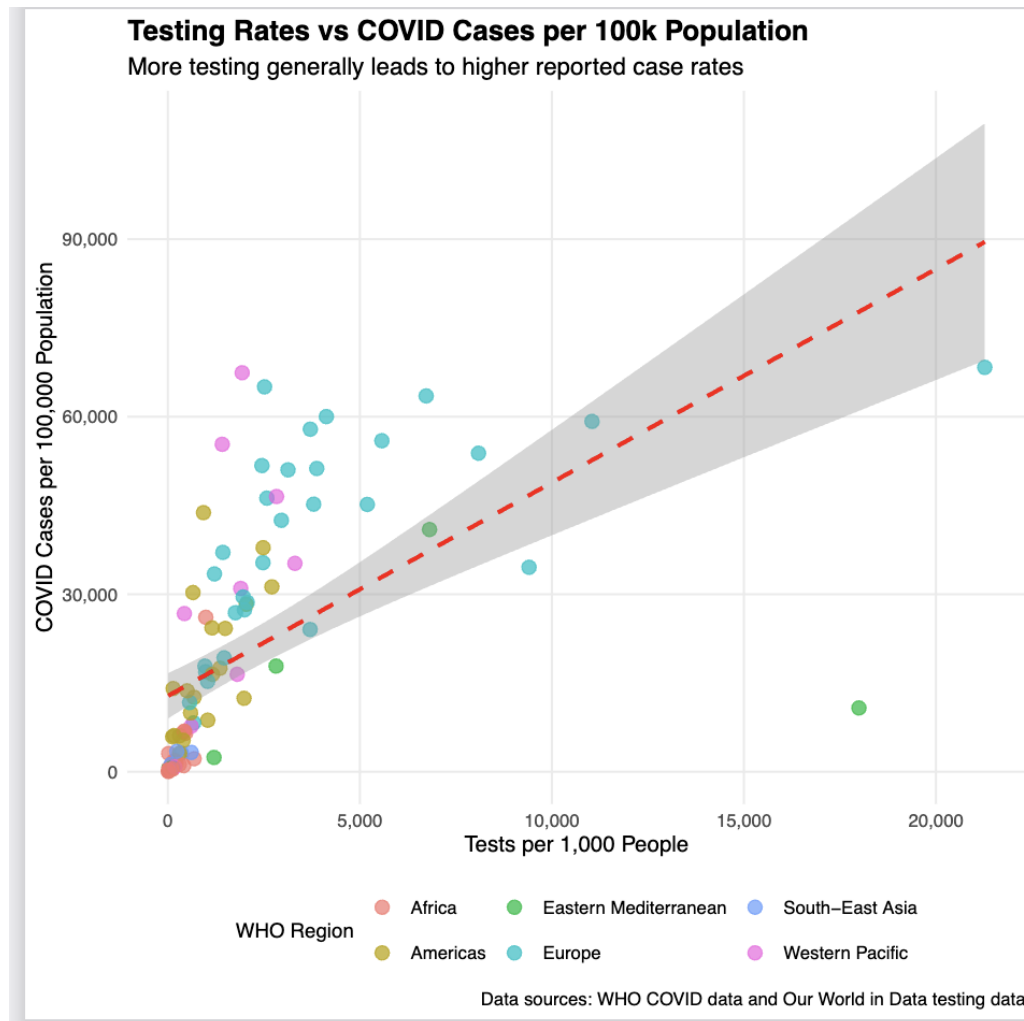


Figure 2: COVID-19 Testing Rates vs COVID Cases per 100k Population across WHO regions

2.3.2 The correlation between GDP per capita and testing performed

Figure 3 demonstrates a positive correlation (Correlation: 0.429) between national wealth and COVID-19 testing capacity, with wealthier countries conducting significantly more tests per capita than their lower-income counterparts. This disparity in testing infrastructure likely contributed to higher recorded case numbers in affluent nations, not necessarily due to greater disease prevalence, but rather enhanced detection capabilities. ****Richer nations take more COVID tests than poorer ones. Hence, they recorded more cases.****

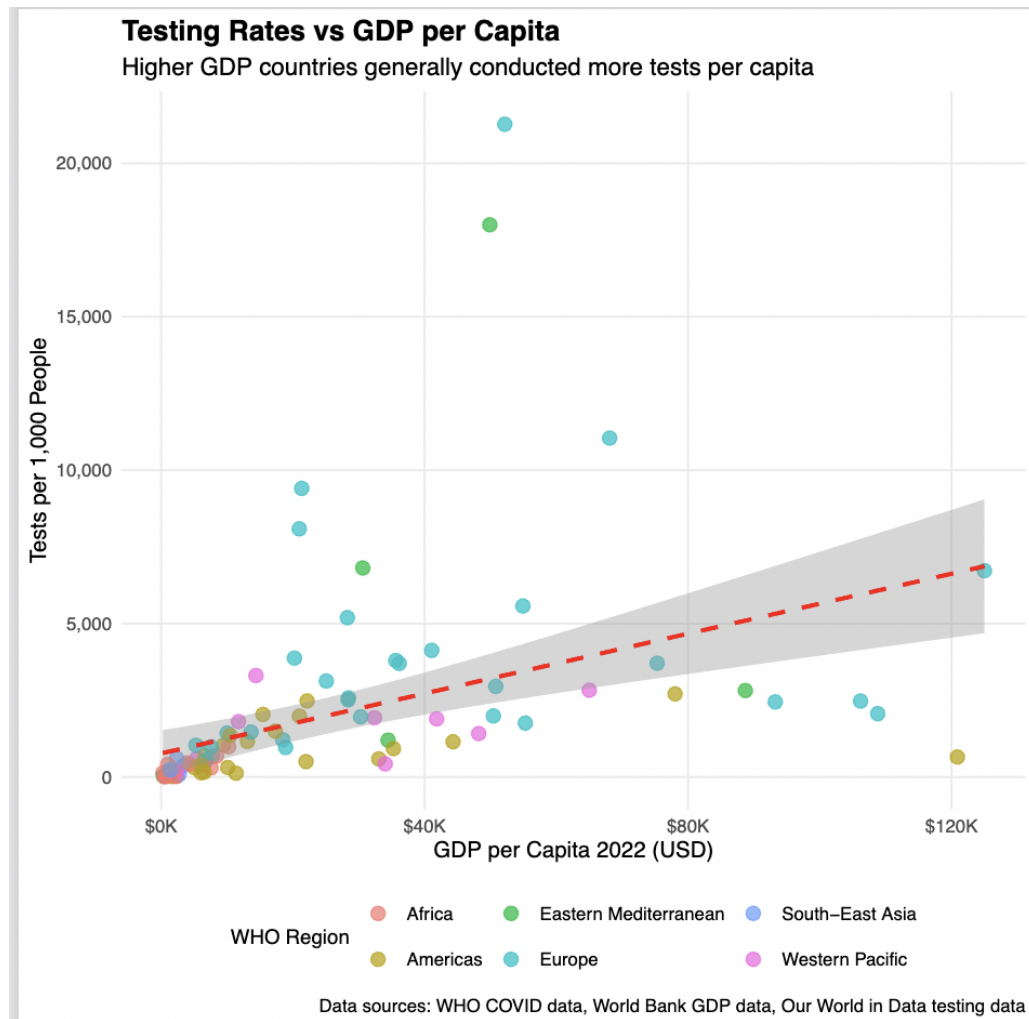


Figure 3: COVID-19 Testing Rates vs GDP per capita

2.3.3 The correlation between GDP per capita and COVID-19 death rates

The scatter plot reveals a negative correlation between national wealth and COVID-19 death rates, demonstrating that wealthier countries achieved significantly better health outcomes despite often recording higher case numbers due to superior testing capacity. This pattern reflects disparities in healthcare infrastructure, medical resources, and pandemic response capabilities between high and low-income nations. Despite having MORE CASES, high-income nations have LOWER DEATH RATE. For instance, extreme cases:

- Highest death rates: Sudan (7.89%), Syria (5.51%), Somalia (4.98%)
- Lowest death rates: Nauru (0.018%), Singapore (0.067%), Iceland (0.088%)

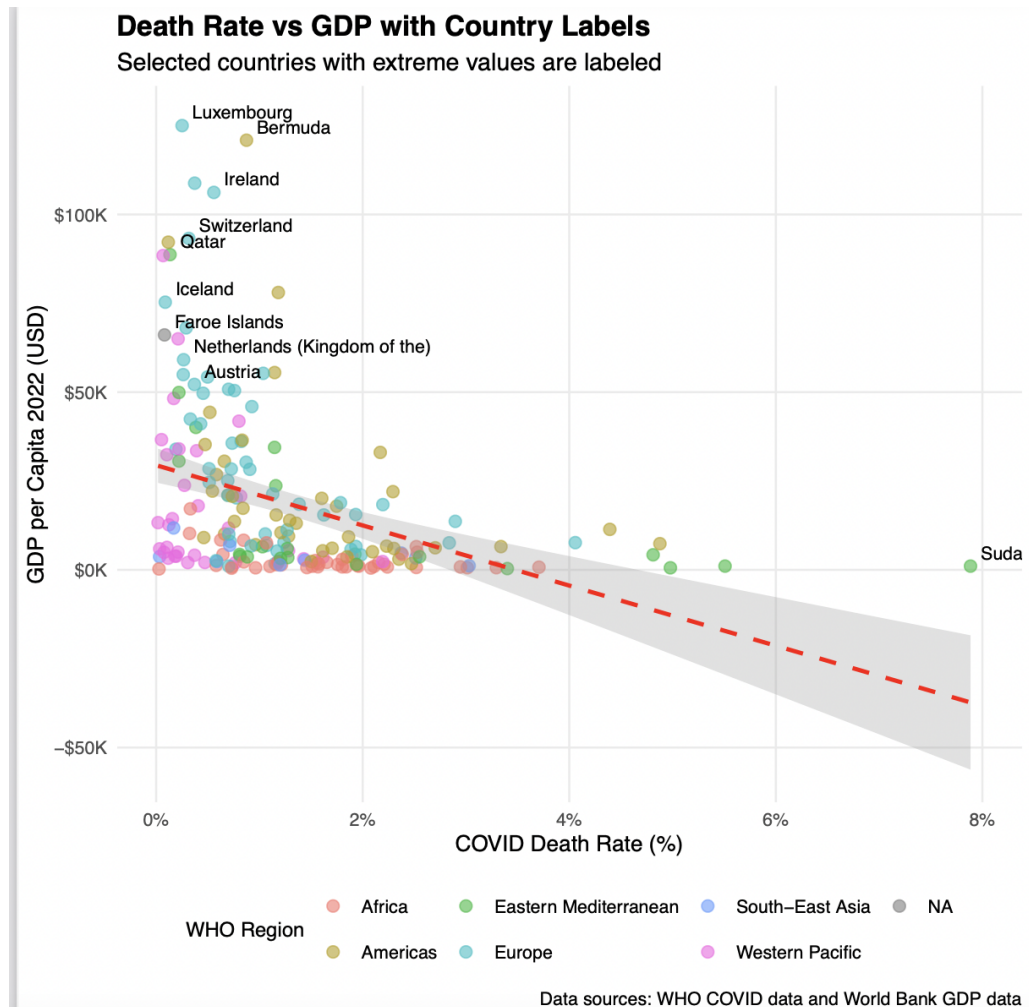


Figure 4: COVID-19 Death rates vs GDP per capita

2.3.4 Question conclusion

In conclusion, the pandemic exposed and amplified existing global health disparities, revealing fundamental inequalities in healthcare infrastructure and pandemic response capabilities. The stark contrast between wealthy and poor nations becomes evident when examining both testing rates and mortality outcomes, highlighting systemic vulnerabilities in lower-income countries. **The COVID-19 pandemic revealed stark global inequalities. Poorer nations were significantly more vulnerable due to two key factors: Limited testing capacity led to widespread underreporting of cases; Weaker health systems resulted in higher death rates and overwhelmed healthcare infrastructure. While, wealthy nations can handle the pandemic better thanks to their strong economic foundation allowing them to perform more tests and provide better treatment for serious cases, thereby reducing death rates.

3 Research Question 2: What patterns can be observed in the rise, peak, and decline of COVID-19 cases across nations, and how can visualizations of these trends help identify commonalities in effective public health responses that contributed to minimizing outbreaks?

3.1 Introduction

COVID-19 emerged over five years ago in China, with global cases peaking in 2022. However, the World Health Organization (2025) recently reported rising cases in multiple regions, including Southeast Asia, alongside new variant emergence. This analysis examines pandemic trends through comparative case studies, identifies patterns among nations with shared backgrounds, evaluates policy responses, and extracts lessons for future preparedness. The analysis focuses on three regional groups: the United States as one of the most severely impacted nations, European Union countries including Italy, Germany, and Spain - one of the first and most affected countries in Europe, and Southeast Asian nations comprising Vietnam, Thailand, and Malaysia. This selection enables examination of how developed nations managed the pandemic and responded and comparison with Southeast Asia, where these nations showed a better response at first but their reaction to later waves of COVID was problematic. The interactive chart allows user to analyze nation or a selection of nations through a timespan to see the differences and similarities in trend, understanding more of those country situation during that time. By examining these case studies through data analysis and policy evaluation, this study seeks to understand the role of timing governmental response, healthcare information during the pandemic.

3.2 Approach

Our approach to analyzing global COVID-19 pandemic trajectories integrates both quantitative data visualization and contextual information. The primary quantitative data is derived from the provided charts, which depict cumulative confirmed cases, recovered cases, and deaths, alongside daily new confirmed cases for the United States. These line charts will be meticulously examined to identify key pandemic phases, including initial surges, peak magnitudes, and subsequent declines, noting specific dates and case numbers. The bar and pie charts offer a static snapshot of the overall burden comparing between selected countries. The final chart shows the daily fluctuations and major peaks of new infections, indicating new waves of the virus.

This visual data will be cross-referenced with the research information through papers, news information for the USA, EU nations (Italy, Germany, Spain), and Southeast Asian countries (Vietnam, Thailand, Malaysia). The text provides crucial qualitative context, detailing governmental policy responses, vaccination rates, the emergence of variants (Delta, Omicron), and socio-political factors. By correlating the quantitative trends from the charts with these qualitative insights, we aim to understand the underlying drivers of each region's pandemic trajectory. The analysis will involve a comparative study across these diverse regions to identify common patterns influenced by viral evolution and unique divergences shaped by specific policy decisions and public health infrastructure.

The full implementation can be accessed in `app.R` file available on our GitHub repository (Section 4).

3.3 Analysis & Discussion

This will be analyzing the data of COVID-19 cases, death, recovered in 3 countries/regions: United States, Europe Union: Italy, Germany, Spain, and Southeast Asia: Vietnam, Thailand, Malaysia

3.3.1 USA

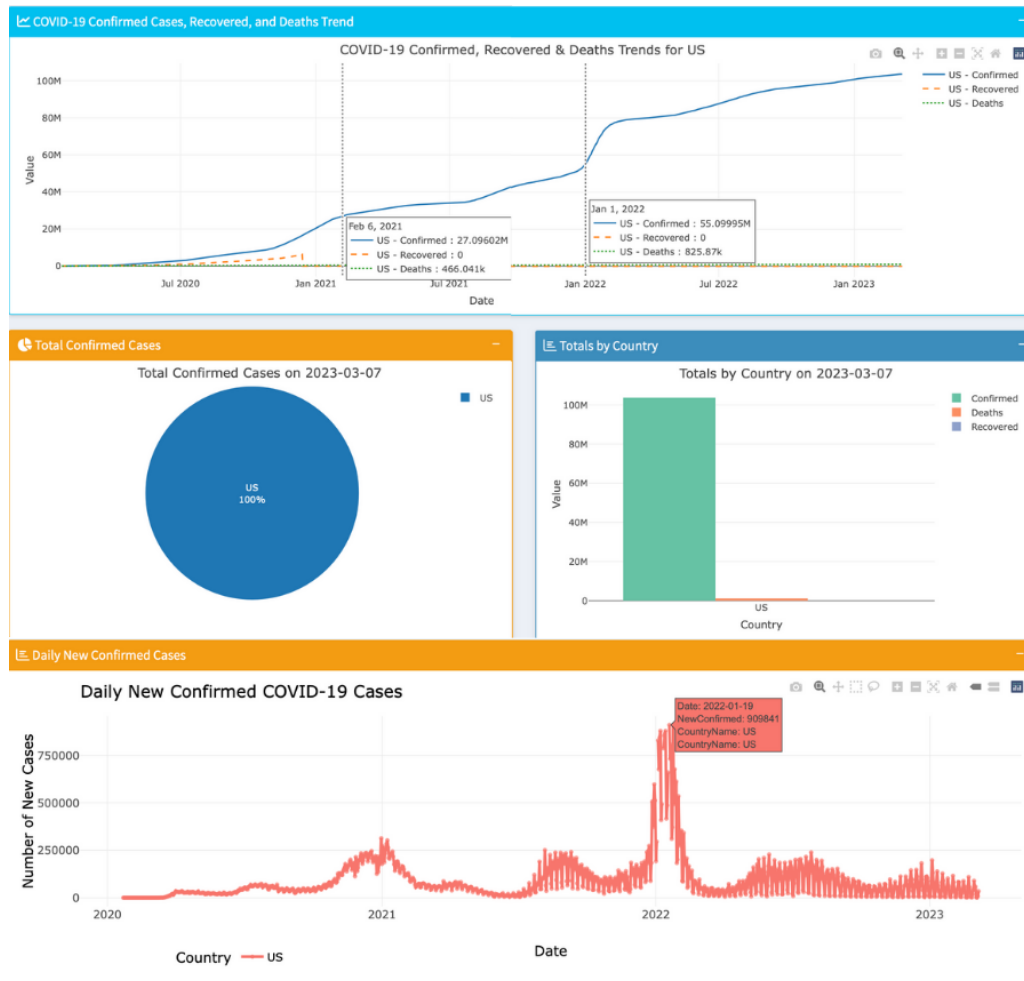


Figure 5: The Progress of COVID-19 in the US.

The United States demonstrated a failed story throughout the COVID-19 pandemic, characterized by multiple waves that mirrored global variant emergence patterns. By 2023, the nation accumulated over 100 million total cases—nearly one-third of its population—establishing it among the most severely impacted countries worldwide. The case distribution shows two critical surge periods: an initial rapid increase around November 2020, peaking December 31, 2020, with approximately 300,000 daily cases, followed by a more dramatic escalation in December 2021, reaching 750,000 daily cases by mid-January 2022.

These patterns were not distinctive to the United States but reflected global trends. The timing appeared consistently across other country groups, explained by new variants—Delta and Omicron—which possessed significantly enhanced infectious capabilities compared to previous strains. This demonstrates how viral evolution, rather than solely domestic policies, shaped the pandemic's trajectory globally.

The United States' severe impact stemmed from fundamental governmental failures during the early response period. Federal coordination was delayed in 2020, accompanied by inconsistent state policies and dangerous underestimation of the virus's potential impact (Wallach & Myeres, 2020). Mixed leadership messages particularly undermined public health efforts. While some states implemented mask mandates, others resisted such measures. President Trump's public reluctance to wear masks, despite evidence of their protective efficacy, created confusion and likely reduced compliance with prevention measures (Rubin et. al, 2020).

When Omicron emerged in late 2021, the United States had established substantial vaccination coverage. However, Omicron's exceptional transmissibility drove cases to unprecedented levels, creating the massive January 2022 peak. The decline by March 2022 was notably rapid, reflecting vaccination and acquired immunity effects. Vaccination data revealed disparities: receipt was lower among those with prior COVID-19 diagnosis compared to those without, with coverage at 73% versus 85% for one dose, and 69% versus 82% for full vaccination respectively (Nguyen, March 2022). The combination of vaccine-induced and natural immunity created population-level resistance that helped contain the Omicron wave's duration.

3.3.2 Europe: Italy, Germany, Spain

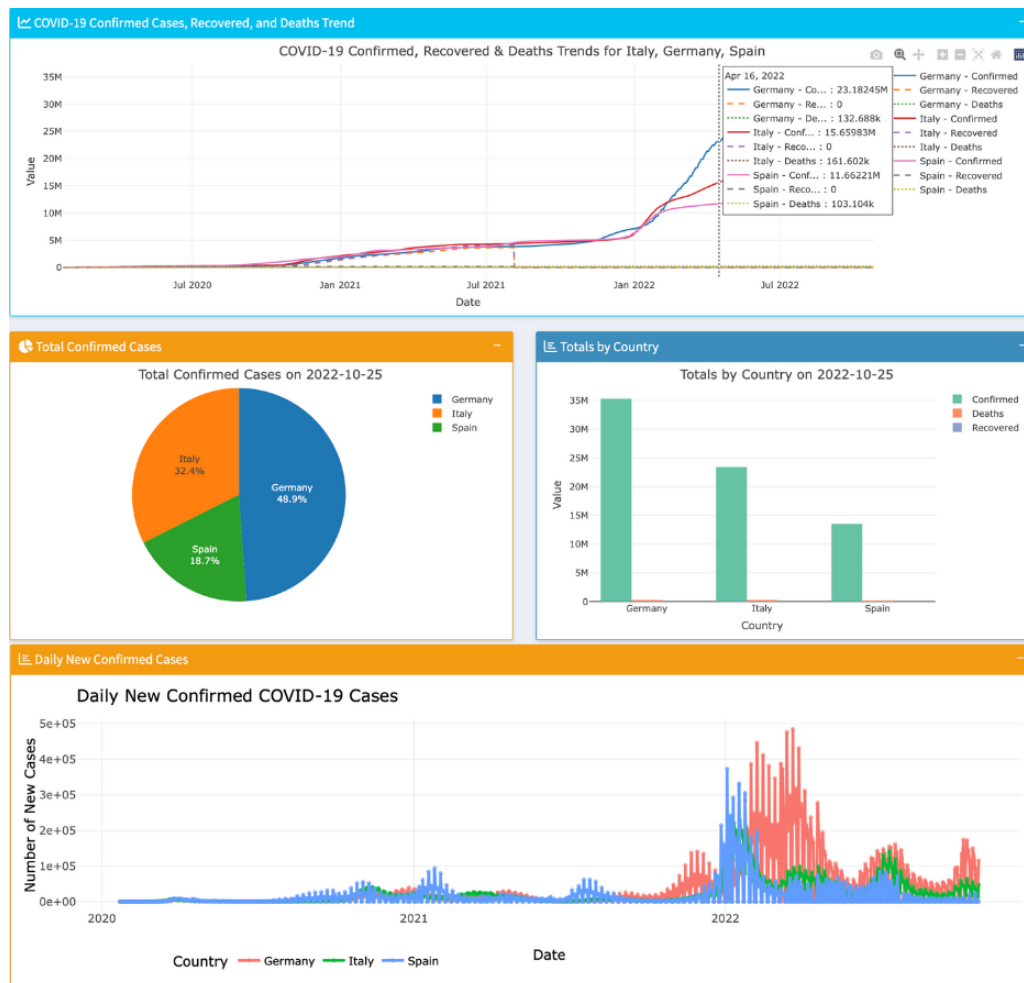


Figure 6: The Progress of COVID-19 in Italy, Germany, Spain.

Major European nations exhibited remarkably similar pandemic trajectories, characterized by initial moderate surges followed by devastating Omicron waves. Italy, Germany, and Spain experienced initial increases during February 2021 with tens of thousands of daily cases, but the real crisis emerged in early 2022. Spain reached its peak in January 2022 with 300,000 daily cases, while Germany's surge came later in mid-February 2022 with 400,000 cases per day—the highest among the three nations. Italy demonstrated a more complex pattern, peaking at 220,000 daily cases initially, then experiencing unusual secondary surges with 150,000 cases in mid-2022 and 200,000 cases in November 2022, suggesting prolonged vulnerability to variant waves.

The severity of these impacts reflects critical early policy failures across the region. Italy implemented lockdown measures on March 9, 2020, followed by Spain on March 14, but these interventions came too late in the transmission cycle. By April 14, both countries had become the two most severely affected

nations in Europe, demonstrating that reactive rather than preventive approaches proved insufficient (Cheng & Khan, 2020). These delayed responses highlight how the timing of intervention measures critically determines their effectiveness.

Despite these initial failures, European Union nations demonstrated significant improvement in their pandemic response infrastructure. Vaccination policies were rolled out relatively rapidly by mid-2021 across all EU nations, with strategic prioritization of vulnerable groups including the elderly and children (Kessel et al., 2023). However, even this improved preparation could not prevent Omicron from overwhelming healthcare capacity, illustrating the variant's exceptional transmissibility.

The eventual decline in cases resulted from multiple converging factors: high vaccine and booster coverage across populations, improved hospital protocols developed through experience, and enhanced antiviral treatments. This multifaceted approach enabled European nations to manage subsequent waves more effectively than their devastating early experience.

3.3.3 Southeast Asia: Vietnam, Thailand, Malaysia

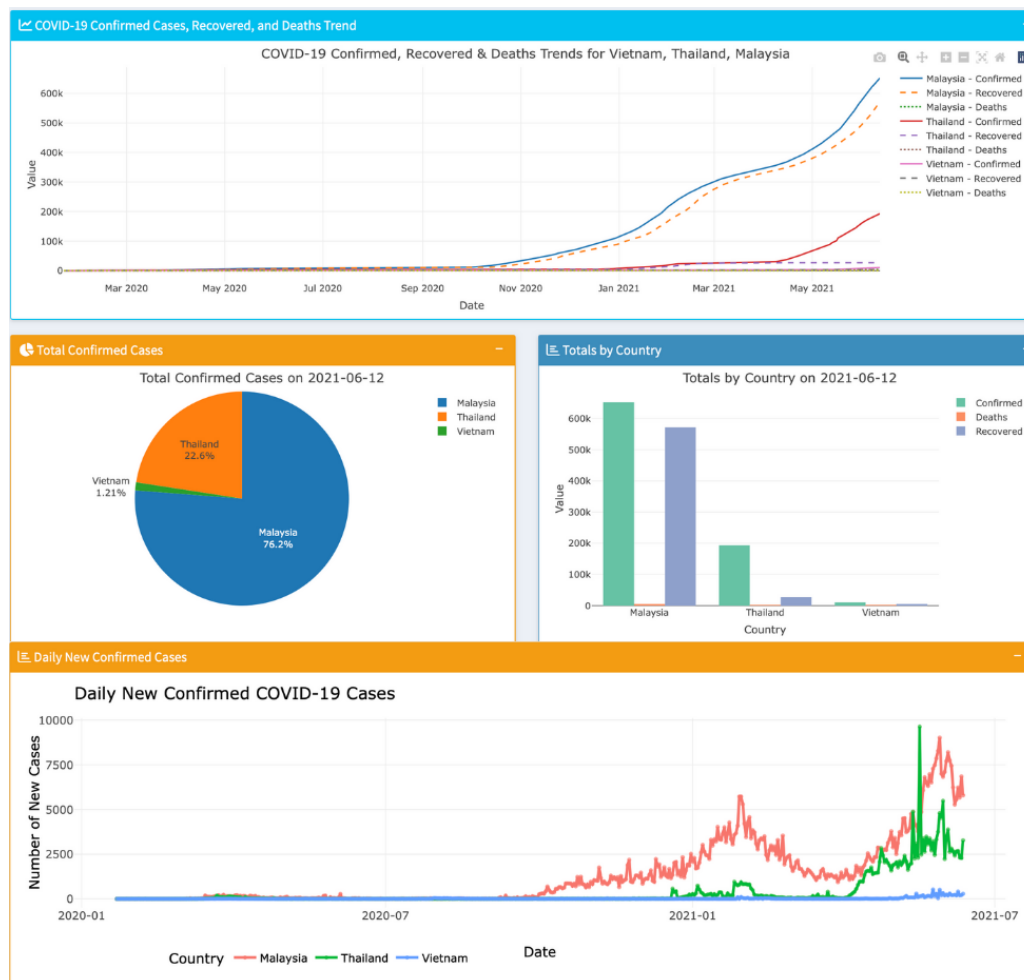


Figure 7: The Progress of COVID-19 in Southeast Asia Countries Prior to July 2021.

Southeast Asian nations demonstrated divergent pandemic trajectories, with Vietnam representing the most dramatic transformation from success to crisis. Vietnam maintained exceptional control through July 2021, with cases remaining in the hundreds while regional neighbors struggled with higher transmission rates. As of July 2021, the situation in Vietnam has gone worse, but comparing to other countries in the region, it was doing significantly well. The number of confirmed cases was really low compared to

the other with 1. 21% while Malaysia accounts up to 76% and 22% in Thailand..



Figure 8: The Progress of COVID-19 in Southeast Asia Countries After July 2021.

However, this early success created a devastating reversal. After July 2021, Vietnam experienced explosive growth reaching tens of thousands of daily cases, coinciding with similar surges in Thailand and Malaysia, which peaked at approximately 12,000 cases per day during the same period. There were fault actions during these time with changes in policy result in this circumstance which will later be discussed. But it has changed significantly as now

Vietnam's trajectory became particularly severe by February 2022, when cases escalated from tens to hundreds of thousands daily. The crisis peaked on March 12, 2022, with 400,000 new cases per day—dramatically exceeding Thailand and Malaysia peaks and representing one of the highest per-capita surge rates globally. This contrasts sharply with Thailand and Malaysia, which managed their surges more effectively during the same timeframe.

Vietnam's initial success story from 2020 to July 2021 resulted from taking the threat seriously due to sharing a border with China, implementing strict early measures (Hutt, 2021). However, this early success created critical vulnerabilities. The low vaccination rate of only 25% in 2021, combined with the Delta variant's emergence, triggered the devastating outbreak (Do et al., 2023). Additionally, previous success bred overconfidence and resulted in medical equipment shortages when the surge arrived (Hoang, 2022).

Recovery came through rapid policy adaptation. Vietnam achieved control with dramatically increased vaccination coverage, reaching a full vaccination rate of 80.1% by April 6, 2022 (Hoang, 2022). The

government's shift to a "new normalization" policy enabled management of later 2022 surges, where cases increased but severe outcomes remained minimal, demonstrating successful transition from elimination to mitigation strategies.

In terms of future prevention of the increasing threats of COVID-19, Vietnam should take an active response on the prevention. Temporarily, the situation has not gotten any worse, however, new information should be updated spontaneously to the citizens so that measurements can be taken by them. Warning on the situation, focus on the vulnerable groups such as the elderly, children, ..., suggest on wearing mask. Reminding people of vaccination, implement a wide range of coverage so that the lesson of crisis during the summer of 2021 would not happen again.

4 Handover

- All project files, documentation, and resources are available in the GitHub repository: https://github.com/tunglambg131003/data_visualization_project_2
- The final deployed product is available at: <https://data-visualization-proj2.shinyapps.io/COVID-19-Shiny-App/>

5 Limitations

Despite being visually informative, the interactive Shiny app has several limitations. First, the data rendered in the app is static and not updated in real time. As a result, any recent developments or changes in COVID-19 case numbers, deaths, or other statistics are not reflected, reducing the app's usefulness for current analysis. Second, while the app effectively presents general trends through charts and an interactive map, its insights are largely descriptive. It focuses on high-level figures such as total deaths and confirmed cases across countries but lacks integration with more detailed or contextual data like testing rates, healthcare capacity, or average recovery times. This limitation restricts the app's ability to support deeper analytical or comparative investigations between nations, especially when assessing the effectiveness of different public health responses or socio-economic factors. Overall, the app is more suitable for general observation than for in-depth epidemiological or policy analysis.

6 Future Directions

This project establishes a foundational platform for more advanced, interactive exploration of pandemic trends and policy responses. A key future direction involves integrating real-time data and predictive modeling, enabling users to simulate public health scenarios under varying conditions. By incorporating contextual variables such as vaccination rates, mobility trends, healthcare capacity, and socioeconomic factors, the tool can support more comprehensive and data-rich interpretations of outbreak dynamics.

Another significant enhancement would be the integration of a Large Language Model (LLM) API, allowing users to interact with the data via natural language queries. For instance, users could ask, "What caused the second wave in Italy?" or "How did Korea avoid a major outbreak early on?"—and receive evidence-based, context-aware responses. This feature would democratize access to complex datasets and improve usability for both experts and the general public.

Expanding the platform to include subnational data, demographic breakdowns, and detailed policy timelines would further enrich its analytical depth. These additions would allow for more localized insights and contribute to better-informed public health strategies. Together, these developments would transform the application into a comprehensive decision-support system for managing current and future global health crises.

7 Conclusion

In conclusion, this project has undertaken a comprehensive exploration of global responses to the COVID-19 pandemic through the development of an interactive RShiny application. By focusing on two core research questions—how a nation’s economic capacity influenced its ability to manage the pandemic and whether discernible patterns emerged in the trajectory of COVID-19 outbreaks—the project offers a multifaceted tool for both visualization and analysis. The application’s animated global map and customizable dashboard provide users with a dynamic interface for examining the temporal and spatial progression of the pandemic across diverse national contexts. These tools not only highlight variations in infection rates and containment success but also underscore the importance of early intervention, public health infrastructure, policy agility, and societal compliance in mitigating the pandemic’s impact.

The visual comparisons between countries—such as those between the United States, European Union member states, and Southeast Asian nations—offer critical insights into how socioeconomic and political factors intersected with public health strategies to shape outcomes. For instance, nations with robust healthcare systems and proactive policy responses often experienced shorter and less severe outbreak peaks, suggesting that economic resources alone were not sufficient without effective governance and communication.

Beyond its immediate analytical utility, the application serves as a platform for continued inquiry. As the global community reflects on the lessons of the COVID-19 crisis, the ability to visualize and compare longitudinal data across regions becomes invaluable for policymakers, researchers, and public health practitioners. Future enhancements—particularly the integration of large language model (LLM) APIs—hold promise for making this data even more accessible and meaningful. Such capabilities could allow users to interact with the dataset using natural language, thereby lowering the barrier to entry for non-technical users and fostering a deeper, more intuitive understanding of complex epidemiological trends.

Ultimately, this project contributes to the growing body of digital public health tools aimed at fostering transparency, insight, and preparedness in the face of global health crises. It underscores the potential of data-driven applications not only to document past events but to inform more effective responses in the future.

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