

# How did local health infrastructure and socio-political factors within different states and counties in the United States affect the disparities in COVID-19 outcomes, and what lessons can be learned for more targeted public health preparedness and response strategies in future pandemics?\*

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\*Code and data are available at: <https://github.com/hannahyu07/US-Covid-Analysis.git>

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## 1 Introduction

*This reproduction was performed after a replication on the Social Science Reproduction platform: [link here](#)*

## 2 Data

### 2.1 Source

The datasets utilized in this paper were mainly obtained from the **original paper** (Nuzzo and Ledesma 2023). The data used by the paper was compiled from various sources such as the Arias et al. (2022), Arias and Xu (2022), Bell and Nuzzo (2021), Systems Science and Engineering (2023), Dong, Du, and Gardner (2020), *COVID-19 Excess Mortality Estimates 2020-2021* (2022), Ledesma et al. (2023), Health Statistics (2022), “Death Rate, Crude (Per 1,000 People) (SP.DYN.CDRT.IN)” (2022), Economic and Division (2022), and Wang et al. (2022). Additionally, to address the original paper’s lack of US COVID statistics and political party support data, we incorporated information from Jack and Oster (2023) and (Elflein 2023). The political party support data we utilized from Jack and Oster (2023) was compiled from McGovern (2009–2020).

Jack and Oster (2023) discusses the long-term impacts of COVID-related school closures. From this source, we utilized the dataset on voting shares during the 2020 election by county. Elflein (2023) summarizes COVID-19 death rates in the United States as of March 2023, organized by state. Analyzing results from both datasets allows us to explore the relationship between political affiliation and COVID-19 outcomes. Our reproduction aims to fill these gaps and includes tables and graphs not presented in the original paper to support our findings.

## 2.2 Methodology

This paper will replicate the data that was originally presented by Nuzzo and Ledesma (2023), as previously mentioned. We then transform the replication to our data analysis incorporating the COVID statistics and political party support data. We seek to use our initial replication and following own data analysis to provide a fresh part of the original paper, enhancing the with more data. Different from the original paper which spent a lot of time talking about how badly prepared the US was against other countries, We also specifically diverge our focus to the political and socioeconomic factors that impacted the US's COVID outcome.

R (R Core Team 2022) was the language and environment used for the bulk of this analysis, alongside `tidyverse` (Wickham et al. 2019), `sf` (Pebesma 2018), `readxl` (Wickham and Bryan 2023), `knitr` (Xie 2014), `janitor` (Firke 2023), `lubridate` (Grolemund and Wickham 2011), `dplyr` (Wickham et al. 2023), `data.table` (Barrett et al. 2024), `RColorBrewer` (Neuwirth 2022), `ggpubr` (Kassambara 2023), `ggplot2` (Wickham 2016), `here` (Müller 2020), `kableExtra` (Zhu 2024), `webshot` (Chang 2023a), `webshot2` (Chang 2023b), `gt` (Iannone et al. 2024) and `scales` (Wickham, Pedersen, and Seidel 2023).

## 2.3 Data cleaning

From all the data provided from Nuzzo and Ledesma (2023), Jack and Oster (2023), and Elflein (2023), we mainly utilize the Bell and Nuzzo (2021), Health Statistics (2022), McGovern (2009-2020), and Elflein (2023). The data from Nuzzo and Ledesma (2023) are quite organized and do not require excessive cleaning for us to proceed.

Since we aim to analyze people's political preferences on a state level and the data we collected from McGovern (2009--2020) is on a county level, we create a new data frame "vote\_data\_by\_state" to summarize all the votes by state. We utilize the "group\_by" function to form new variables on a state level. We calculated each the sum of the total votes, total Republican party votes, total Democratic party votes, and total vote difference between the two parties by county and created new variables that calculate the sum of each of these. We also create variables on the average percentage of votes each party receives and the difference by each state.

To find the total number of votes in the Top 10 states with the highest proportion of Republican votes, we create another new data frame "sorted\_states" from the "vote\_data\_by\_state" data frame. We include a new variable "proportion\_republican" that calculates the proportion of votes the Republican party receives from each state and orders the states by the highest proportion of Republican votes. The data from Arias and Xu (2022) does not have column names for each column. To retrieve data by column we assigned column names "State" and "Death\_Rate" to the variables of interest. And then, to find the top 10 states with the highest death rates, we ranked the states based on death rate. Lastly, to create the final figure that incorporates the COVID death rate and people's political preference by state, we merged the

two data from McGovern (2009--2020) and Elflein (2023). And subsequently did our work from there.

## **2.4 Data Measurement**

### **2.4.1 Measurement Techniques**

Manual Data Extraction involved careful review of reports and tables to ensure accurate data capture, particularly for datasets like life expectancy where this meticulous approach was paramount; this was coupled with Standardization and Adjustment processes where excess death data and age-standardized excess death rates underwent significant processing, including the comparison of observed deaths during the pandemic to expected deaths based on historical trends, with adjustments made for the age distribution of the population; concurrently, Geospatial Data Handling was employed for mapping the GHS Index scores, utilizing Geographic Information Systems (GIS) to visually represent pandemic preparedness across various countries, and this was complemented by Real-Time Data Aggregation, which entailed aggregating COVID-19 death data in real-time from authoritative sources such as the Johns Hopkins University Dashboard, necessitating continuous data monitoring and updates to maintain accuracy and relevance.

### **2.4.2 Adjustments and Considerations**

Accounting for underreporting through the measurement of excess deaths provides a more comprehensive view of the pandemic's impact by capturing deaths that may have been missed or misclassified as COVID-19, while the process of age standardization adjusts these excess death rates to a standard age distribution, enabling meaningful comparisons between countries with varying demographic profiles. However, the analysis had to navigate challenges associated with varying data quality and availability across different countries, especially given the diverse COVID-19 reporting standards and testing capacities. Moreover, the study also acknowledges the significant influence of political and social factors on the pandemic's outcomes, which, despite being more challenging to quantify, are essential for a holistic understanding of the pandemic's impact.

## **3 Results**

Our results are summarized in the following figures. Figure 2 illustrates the trend of life expectancy at birth across different racial groups over time. Table 2 provides a more detailed breakdown of the life expectancy before and during COVID for Asian, American Indian, Alaska Native and other racial communities.

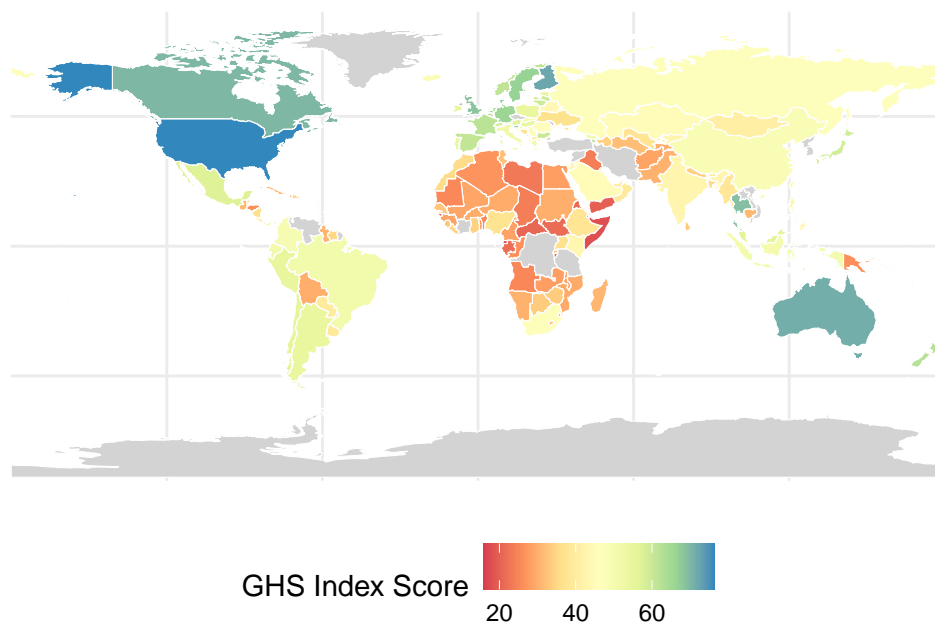


Figure 1: Global Health Security Index Scores by Country

Figure 1 also allows us to visualize the Global Health Security (GHS) Index which is designed to assess a country's capabilities to prevent, detect, and respond to significant infectious disease outbreaks. A higher Global Health Security (GHS) Index score indicates a stronger health system capacity for pandemic readiness. The GHS Index assesses the readiness of countries for pandemics and other significant biological threat emergencies, using a comprehensive framework that includes measurements grouped into six broad categories: prevention, detection, response, health system capacity, compliance with international norms, and risk environment. Higher scores suggest that a country has a more robust health system capacity, with better capabilities to prevent, detect, respond to, and mitigate the spread of an epidemic.

Conversely, a lower GHS Index score implies weaker health system capacities, suggesting that the country may be less prepared to handle pandemics and other significant biological threats. Lower scores indicate deficiencies in one or more of the critical areas assessed by the Index, which could potentially hinder the country's ability to effectively manage and control the spread of infectious diseases.

Unfortunately, due to the unavailability of data over time for Asian, American Indian, and Alaska Native communities, they have been excluded from the time series graph.

An intriguing observation is the consistently higher life expectancy among Hispanic individuals compared to other groups, even amidst the challenges posed by COVID-19. On the other hand, Black individuals have consistently exhibited lower life expectancy, which further declined

notably in 2021, reaching just over 70.8 years old. The life expectancy trends of white people and all other races and origins remain close together throughout the 14 years, with minimum variance. Specifically, the life expectancy for White individuals decreased from 78.8 to 76.4 years old from pre-pandemic levels in 2019 to 2021, while for Hispanic individuals, it dropped by 4.2 years, and for Black individuals, it declined by 4 years during the same period.

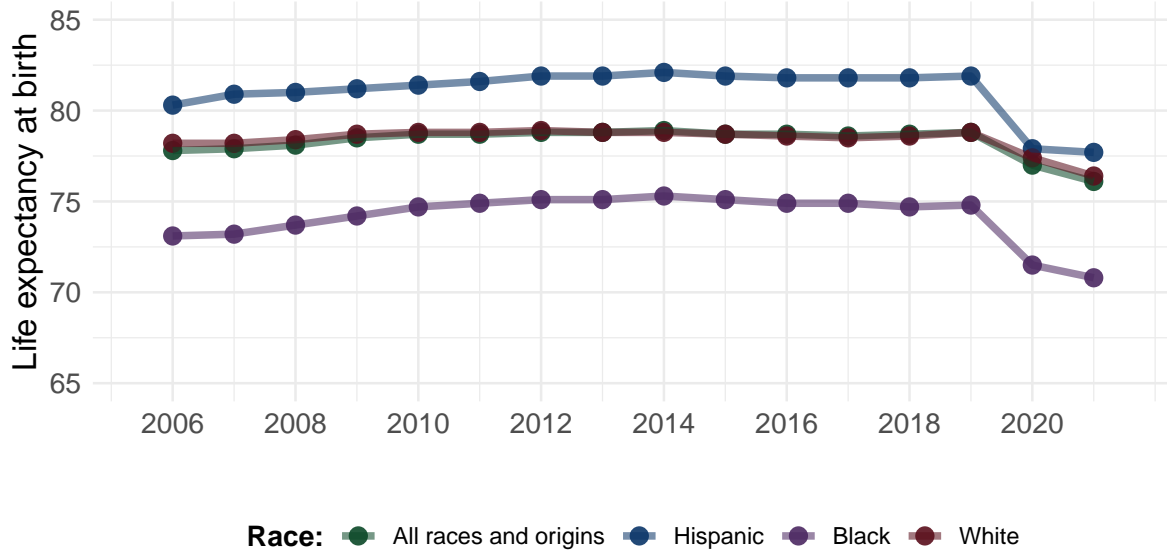


Figure 2: Estimates of Life Expectancy at Birth, by Race 2006-2021

Table 1: Top 10 States with Highest Death Rates from COVID-19 (per 100,000 people)

Rank	State	Deaths
1	Arizona	455
2	Oklahoma	454
3	Mississippi	449
4	West Virginia	444
5	New Mexico	432
6	Arkansas	431
7	Alabama	429
8	Tennessee	428
9	Michigan	423
10	Kentucky	406

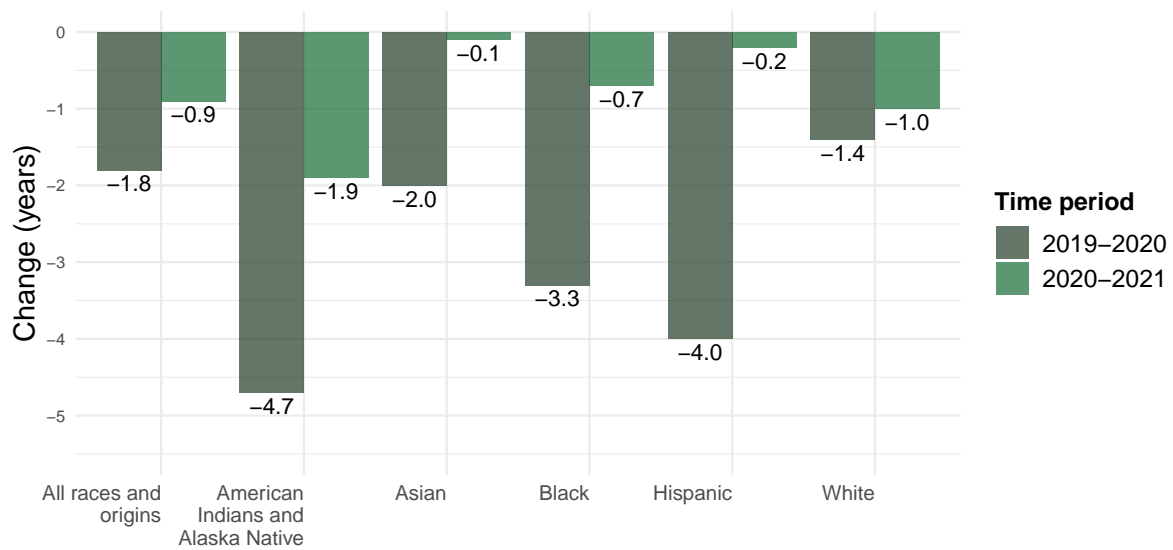


Figure 3: Change in Life Expectancy at Birth from the Previous Year

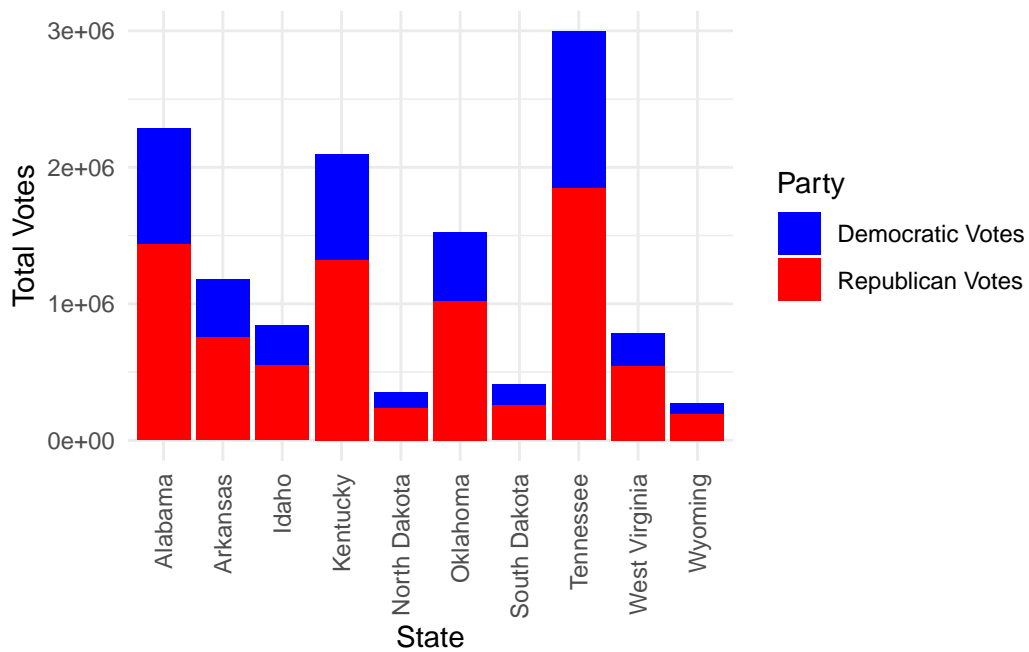


Figure 4: Total Number of Votes in Top 10 States with Highest Proportion of Republican Votes

Table 2: Life Expectancy by Race (2019-2021)

Year	All races and origins	Hispanic	AIAN	Asian	Black	White
2019	78.8	81.9	71.8	85.6	74.8	78.8
2020	77.0	77.9	67.1	83.6	71.5	77.4
2021	76.1	77.7	65.2	83.5	70.8	76.4

Figure 3 serves as a valuable addition to our previous analysis with the inclusion of Asians, American Indians, and Alaska Natives during the critical period from 2019 to 2021. With these additional ethnic categories, we can discern that American Indians and Alaska Natives experienced significant impacts from the pandemic, with a decrease of 4.7 years in the first year and 1.9 years in the second year, totaling 6.6 years.

With a chart that depicts the change in life expectancy each year by ethnicity, we can better gain a more comprehensive understanding of the impact of COVID by ethnicity. While the declines in life expectancy are smaller in magnitude from 2020 to 2021, they are notably minimal for Asians and Hispanics, with reductions of -0.1 and -0.2 years respectively. (Insert some sources tmrw)

Numerous sources have indicated a correlation between a state’s political affiliation and its handling of COVID issues (sources to be inserted tomorrow). To testify to the claim, we collected the voting data for each of the 50 states for the 2020 presidential election. We then selected the ten states with the highest proportions of Republican votes. These voting patterns are visualized in Figure Figure 4, where red symbols represent Republican votes and blue symbols represent Democratic votes. Among the top ten states, Tennessee recorded the highest total number of votes, while Wyoming boasted the highest proportion of Republican votes.

Given the variation in population sizes among states, direct comparisons of COVID-19 case numbers are inherently flawed. As an alternative, we employed death rates per 100,000 people as a metric for evaluating each state’s COVID preparedness and situation. We then produced Table 1 that rank the top ten states with the highest death rates from COVID-19 per 100,000 people to examine the potential correlation between party preferences and COVID-related deaths. Notably, We found that six of the ten top Republican states made a reappearance in the top death rates table; these states are Oklahoma, West Virginia, Arkansas, Alabama, Tennessee, and Kentucky. (Insert quotes about the republican party and COVID tmrw)

Following our previous analysis regarding individuals’ political affiliations, we have developed Figure Figure 5, which encompasses all 50 states of the US along with their political leanings based on which party garnered the majority votes. This information is juxtaposed against their respective COVID-19 death rates.

While we cannot make any definitive assertions about stark differences, we do observe that the Republican-leaning states are slightly more clustered around higher death rates ranging from



350 to 450 deaths, while the Democratic-leaning states appear to be more evenly distributed, and notably one Democratic-leaning state has the lowest death rate. An intriguing observation is that although many Republican-leaning states demonstrate higher COVID death rates, it is noteworthy that Arizona, typically considered a Democratic-leaning state, records the highest death rate among all states.

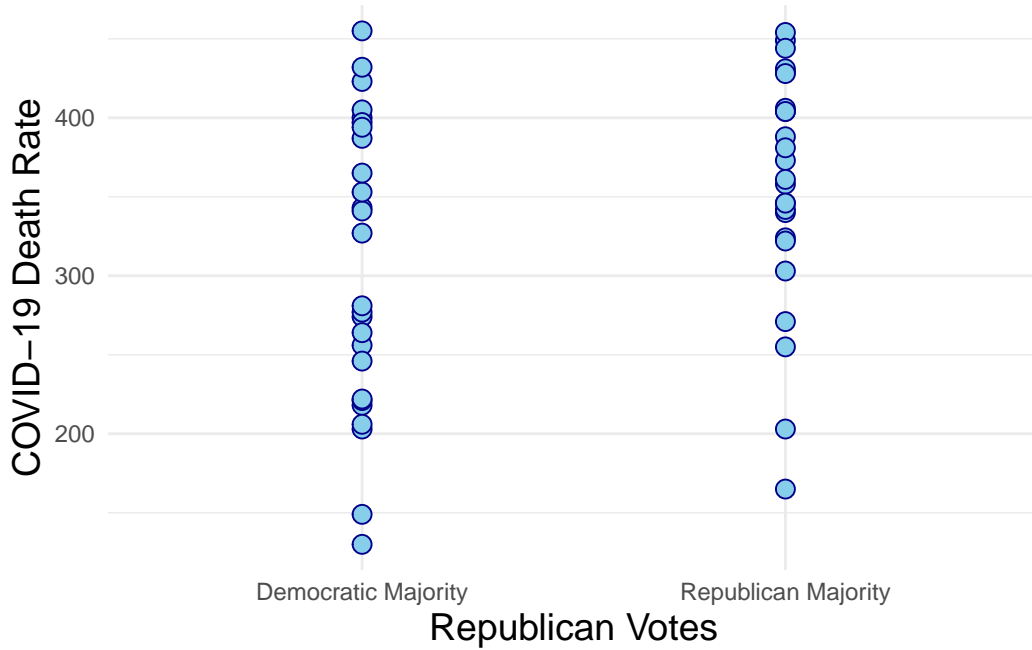


Figure 5: COVID-19 Death Rates vs. Republican Votes

## 4 Discussion

This begs the question as to why we are seeing these results. There isn't exactly a single answer to this question, however, we can certainly point out some considerable factors to this result.

### 4.1 Influence of political polarization on adherence to health guidelines.

Political polarization has significantly impacted the adherence to health guidelines during the COVID-19 pandemic. The divergence in political ideologies has translated into differing attitudes towards health directives, including mask mandates, social distancing, and vaccination uptake.

Various studies and our results have shown that areas with higher support for one political party exhibited distinct behaviors and compliance levels with health recommendations, which directly correlated with COVID-19 case rates and mortality. A news article from *ABC News* (Diab and Kumar 2023) shows that the top states with the highest COVID-19 deaths are Arizona, and Washington with 581 deaths and 526 deaths respectively per 100,000 people. According to 2020 presidential voting data published by CNN, we have both states having the electoral vote of Democrat with Washington winning by 58% (*2020 Election Results by State, Washington* 2020) and Arizona winning by 49.4% (*2020 Election Results by State, Arizona* 2020). Another news article by *ContagionLive* (Parkinson 2023) also claims both Arizona and Washington have the highest COVID-19 mortality. This polarization has not only influenced individual behavior but also shaped state and local health policies, further entrenching the disparities in health outcomes.

The adherence to health guidelines is evident in the varied health outcomes observed across the United States. Regions with lower compliance to health directives, often influenced by political leanings, have experienced higher rates of COVID-19 transmission, hospitalizations, and deaths. The disparities in vaccine uptake, driven by political affiliations, have further exacerbated these outcomes, leaving certain communities more vulnerable to the virus and its variants. To mitigate the influence of political polarization on public health, it is imperative to depoliticize health guidelines and focus on evidence-based approaches to disease prevention and control. Building trust in health institutions and promoting bipartisan support for public health measures are essential steps toward achieving higher compliance and better health outcomes. Engaging trusted community leaders and utilizing targeted communication strategies can also help bridge the divide and encourage adherence to health guidelines.

## **4.2 Impact of government transparency and consistent communication on public trust.**

The politicization of health guidelines and mixed messages from political and health leaders during the COVID-19 pandemic have significantly undermined the effectiveness of public health messaging, leading to confusion, skepticism, and eroded trust among the public. Initially, inconsistencies in recommendations, such as on mask usage, challenged the principle of clear, consistent, and science-based communication essential for an effective public health response. Moreover, the transparency of government actions and decision-making processes is crucial in building and maintaining public trust, especially during health crises. The level of public trust was greatly affected by the openness and accuracy with which governments, at all levels, communicated about the evolving situation, the reasoning behind guidelines, and the measures taken to combat the virus, emphasizing the importance of transparent reporting of data related to case counts, hospitalizations, vaccine distribution, and side effects. Furthermore, consistent communication from public health officials and government leaders is key to ensuring adherence to health guidelines, where inconsistencies, such as changes in mask-wearing guidelines without clear explanations, have led to public confusion. The direct

correlation between government transparency, consistent communication, and public behavior is self-evident, with populations receiving clear and transparent information being more likely to adhere to guidelines, participate in testing and tracing efforts, and accept vaccination. Drawing lessons from the pandemic, strategies for improving government transparency and communication in future health emergencies should include establishing centralized information hubs, ensuring regular and predictable communication from health authorities, engaging community leaders in information dissemination, and harnessing digital platforms and social media to amplify public health messages, thus reinforcing public trust and compliance.

### **4.3 Role of social vulnerabilities and healthcare access disparities in pandemic impact**

The COVID-19 pandemic starkly highlighted how social vulnerabilities and disparities in healthcare access exacerbated the impact of global health crises, contributing to significant variations in disease outcomes and underscoring the need for targeted public health strategies that address these disparities' root causes. Social vulnerabilities, such as socioeconomic status, race, ethnicity, and housing conditions, critically determined COVID-19 outcomes' severity, with populations in crowded housing, limited access to sanitation, and lower socioeconomic brackets experiencing higher transmission rates due to social distancing and hygiene maintenance challenges. An independent study done by the **Government of Canada** states that it "identified that the risk of COVID-19 related deaths in Black, Asian and minority ethnic groups was nearly 1.5 times higher than White individuals" (Emily Thompson 2021). Another news article done by the MSN (Dr. Sushama R. Chaphalkar 2024) states that 'racial minority participants reported more negative impacts on health status, activity, and absence from work as compared to the White population.' The pandemic's economic toll further limited these groups' healthcare access, amplifying vulnerabilities. Disparities in healthcare access played a significant role in influencing COVID-19 morbidity and mortality, with communities facing healthcare facility shortages, provider scarcities, and barriers due to insurance or financial constraints at heightened risk. These disparities were evident in the uneven vaccine distribution and access, highlighting the advantages of regions with strong healthcare infrastructure. Marginalized populations, including racial and ethnic minorities, faced compounded risks from social vulnerabilities and healthcare disparities, evidenced by higher infection, hospitalization, and death rates due to factors like essential service employment and prevalent pre-existing conditions. A news article from CNN (Powell 2020) talks about how many essential workers, who cannot work from home, are from black and Latinx communities. These include healthcare professionals, grocery cashiers, delivery workers, and public transport employees. Despite their crucial roles, they often lack adequate pay, protection, and respect. Addressing these disparities in future pandemics requires public health strategies that prioritize equity and inclusivity, including community-based healthcare investments, enhanced vulnerable community outreach, and equitable healthcare resource access policies. By incorporating social determinants of health into public health preparedness plans, responses can effectively protect at-risk

populations, making future public health responses more resilient, inclusive, and effective in safeguarding all population segments.

#### **4.4 Strategies for improving real-time data collection and sharing for public health decisions.**

To address the fragmentation in data collection and sharing witnessed during the pandemic, it's crucial to establish integrated data platforms that enable seamless health data exchange among various health agencies and stakeholders, utilizing cloud computing and APIs for real-time accessibility and usability. Equally important is enhancing data standardization and interoperability through universal standards like FHIR (Fast Healthcare Interoperability Resources) to facilitate efficient data sharing (*What Is FHIR?* 2023). Investing in digital surveillance systems, which employ AI and machine learning to sift through diverse data sources for early outbreak detection, is essential for rapid response to health threats. Furthermore, fostering public-private partnerships can harness the agility of the private sector and the public health expertise of governmental agencies to enhance data analytics capabilities. Ensuring the privacy and security of health data through robust governance frameworks and advanced encryption is paramount to maintaining public trust. Engaging communities in these initiatives ensures their relevance and fosters trust while building global data-sharing networks encourages international collaboration, crucial for a concerted response to pandemics. Collectively, these strategies are fundamental to bolstering public health decision-making and preparedness, making our health systems more resilient against the challenges posed by emerging infectious diseases.

#### **4.5 Weaknesses and next steps**

In our research, we identified several weaknesses that underscored the gap between the U.S.'s high pandemic preparedness ranking and its actual response to the COVID-19 crisis. Notably, there was a significant underutilization of preparedness capacities, as the resources and infrastructures in place were not fully mobilized or applied effectively during the pandemic. This disconnect highlights a critical area for improvement in aligning preparedness with real-time response capabilities. Furthermore, the response inadequately addressed intrinsic social vulnerabilities, exacerbating disparities in healthcare access and outcomes among different racial and socioeconomic groups, and underscoring the need for more inclusive and equitable public health strategies. The heavy politicization of the pandemic response, coupled with inconsistent messaging from health authorities, significantly eroded public trust and compliance, emphasizing the importance of depoliticizing public health measures and enhancing communication strategies. Additionally, shortcomings in data and surveillance systems, including delays in testing, inadequate genetic sequencing, and a lack of comprehensive surveillance, hindered informed decision-making and targeted interventions, pointing to a crucial need for investment in data infrastructure and capabilities. The analysis also suggests that the U.S. could benefit

from more robust international benchmarking and learning from the diverse responses of other countries to health emergencies, which would involve understanding different strategies and their effectiveness beyond mere outcome comparisons.

To address these challenges and strengthen the nation’s resilience to future health emergencies, several next steps are recommended. Strengthening the linkages between preparedness and response is imperative, ensuring that capacities are not only available but also readily deployable and adaptable to the dynamics of a health crisis. This includes fostering agile and responsive systems capable of rapid mobilization. Addressing the social determinants of health is essential, with strategies aimed at mitigating the impact of social vulnerabilities through equitable healthcare access, support for marginalized communities, and targeted protective measures for vulnerable populations. Enhancing communication and public trust is vital, necessitating clear, consistent, and transparent communication from health authorities, alongside efforts to depoliticize health measures. Improving data and surveillance systems is critical to providing real-time insights, expanding genetic sequencing capabilities, and establishing standardized data protocols. Lastly, actively engaging in global health networks to exchange experiences, learn from global successes and failures, and collaborate on best practices is crucial for a more effective and equitable response that maximizes the full potential of preparedness capacities.

## 5 Conclusion

Despite the United States’ top ranking in the Global Health Security Index as the most prepared nation for pandemics, its actual response to the COVID-19 pandemic fell short of expectations, leading to disproportionately high death rates. This discrepancy is attributed to several critical factors highlighted in the paper. The U.S. did not fully capitalize on its pandemic preparedness resources, with early testing blunders and a lack of a unified national testing approach hindering its response. Additionally, inherent vulnerabilities such as the significant portion of the population in congregated settings like nursing homes and prisons increased susceptibility to virus spread and severe health outcomes. The politicization of the pandemic response further compounded these issues, resulting in varied adherence to public health guidelines across states and political lines, thereby undermining the response’s effectiveness. Moreover, inconsistent public health communications and the challenge of accessing standardized, quality data impeded the implementation of localized, effective interventions. The pandemic also highlighted and intensified existing socio-economic disparities, disproportionately impacting marginalized communities who faced higher risks and adverse outcomes, a situation that the response efforts failed to sufficiently mitigate.

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