SANTA CLARA UNIVERSITY

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY

Olivia Figueira
Yuka Hatori
Liying Liang
Christine Chye

ENTITLED

Understanding COVID-19 Public Sentiment Towards Public Health Policies Using Social Media Data

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Yuhong Liu

Thesis Advisor

Nam Ling
Nam Ling (Jun 7, 2021 14:51 PDT)

Department Chair

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Olivia Figueira
Yuka Hatori
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Christine Chye

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Olivia Figueira
Yuka Hatori
Liying Liang
Christine Chye

Department of Computer Science and Engineering
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ABSTRACT

With the outbreak of the COVID-19 pandemic, an overabundance of information related to the virus was released through social media. While more information can ultimately help people learn about the virus and how to protect themselves from it, there has been a lack of uniformity amongst individual states and the federal government in regards to policies and health guidelines (69), which may lead to the public being confused on the best guidelines to follow. There has also been an ideological divide driven by political polarization in the US on how to respond to this pandemic, causing greater contention (17; 86; 37; 46). Analyzing the public's response to COVID-19 state-level policies on social media can help us to better understand the progression of the pandemic in the US.

We analyze public sentiment from Twitter, Facebook, and Reddit data related to policies such as shelter-in-place orders, fall school reopening guidelines, and face mask guidelines using machine learning sentiment analysis methods and compare the results by performing significance testing. We use the COVID-19 cases and deaths and state demographics to analyze and contextualize the results during the timelines that these social media posts were published. We found that users had more positive sentiments in response to mask policies than to shelter-in-place and fall school reopening policies and that there are statistically significant differences in public sentiment when comparing the same policies between several states. Finally, we found that when testing the significance of sentiment differences for different policies within the same state, the majority of the statistically significant differences were found within states that were considered to be swing states in 2020. We suggest that further research be done to analyze why these differences exist and what factors may impact public sentiment regarding COVID-19 public health policies.

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Chapter 1

Introduction

1.1 Problem Statement

Due to the outbreak of COVID-19, an overabundance of information related to the virus was released through social media, putting the world into two concurrent pandemics—COVID-19 and an "infodemic," a term used to describe the phenomena of increased misinformation spread during disease outbreaks (74). As the situation worsened in the US throughout the spring and summer of 2020, people began relying more heavily on the advice publicized by their state and national leaders, such as governors, public health officials, and the President (91). While more information can ultimately help people learn about the virus and how to protect themselves from it, there has been a lack of uniformity between individual states and the federal government in regards to policies and health guidelines (69), which may lead to the public being confused on the best guidelines to follow. In addition to more information being spread on social media, there has been an ideological divide driven by political polarization in the US on how to respond to this pandemic, causing greater contention (17; 86; 37; 46). Analyzing the public's response to COVID-19 state-level policies on social media can help us to better understand the progression of the pandemic in the US and how to better communicate with the public in the interest of public health.

1.2 Related Work

1.2.1 Social Media Studies and Public Health Messaging

Social media is a valuable resource for gaining insight into public discourse, and various influential platforms such as Twitter, Reddit, Facebook, YouTube, and Instagram facilitate such discussions. People use social media to converse, especially during disasters; during Hurricane Sandy, 11 million tweets were posted in just a few days following the event, as was found by Mukkamala and Beck (81). Twitter offers a wealth of knowledge for social media research, and because Twitter allows curated access to large amounts of data, Wang et al. (63) were able to analyze the "infodemic" as well as sentiment analysis of COVID-19 health discussions and potential factors associated with fluctuations in health beliefs on social media, such as case and death statistics, systematic interventions, and public events.

There are several related works that have utilized social media to better understand public opinion regarding a range of topics. Chun et al. (92) tracked user tweets from all over the US related to COVID-19 in order to analyze sentiments which reflected the degree of concern users felt toward COVID-19. Eghtesadi and Florea (58) gathered tweets related to COVID-19 and analyzed user sentiment, and found that the main issues that users discussed included health care, environment, emotional support, business economy, social change, and psychological distress. They suggest that physicians disseminate information to the general public by managing Facebook pages as "influencers" who could be judged as trustworthy (58). Every effort in successfully communicating with the public is vital in such a turbulent political environment and public health crisis. Gadarian et al. (94) conducted an original survey of 3,000 American citizens between March 20-23 of 2020 to understand whether politics could play a role in how people respond to policies. Their findings showed that President Trump was such a popular figure amongst Republicans and so unpopular amongst Democrats that his position on any coronavirus-related issue could have been enough to cause individuals to determine their own position, regardless of whether it aligned with the traditional position of their respective political party. Other studies have shown that COVID-19 news was highly politicized and polarized on the news, both in television news broadcasts and printed newspapers (37; 86). Hart et al. (86) found that the high degree of politicization and polarization during the initial news coverage of COVID-19 may have contributed to the overall polarization of people's attitudes toward this virus.

Cinelli et al. (74) analyzed public health messaging regarding COVID-19 in spring of 2020 on five social media platforms: Twitter, Instagram, YouTube, Reddit, and Gab. The researchers assessed user engagement and interest about the topic of COVID-19 from a varying user base in order to more accurately assess general sentiment. They analyzed over eight million posts from January and February and found that social media plays a "pivotal role in information and misinformation spreading" (74). Beyond public health messaging, which is used to help the public, misinformation and bad actors spreading dangerous agendas are a growing concern for social media platform users, researchers, and public health officials alike. While it is concerning that the top ten misinformation videos regarding COVID-19 had the highest share count on Twitter, Facebook, and Reddit (36), which could suggest that the effects of misinformation are devastating, research on Facebook posts showed that misinformation is actually a deterrent to engagement when compared with posts from friends and family, as was found by Berriche and Altay (42). Finally, Hsian et al. (93) show that anti-contagion policies significantly reduce the growth rates of COVID-19, and therefore the public's response is vital in preventing the spread of the virus.

Researchers have made a concentrated effort to contribute to public health messaging efforts regarding COVID-19 by understanding how people respond to information, what they are concerned about, and what factors may change their opinion and consequently their actions. This data is vital in keeping people healthy and safe, and can aid in future attempts to improve and streamline the process of effectively communicating critical information to the masses. Since none of these related works have specifically analyzed governors and state-level policies, we contribute to this field by focusing on the role that state governors play in the dissemination of public health messaging during the COVID-19 pandemic.

1.2.2 Sentiment Analysis Models

Sentiment analysis with natural language processing (NLP) is the primary way researchers have gathered public sentiment from social media. Stokes et al. (49) suggest that public responses to the deluge of information during the COVID-19 "infodemic" is important but undermeasured. They analyzed public discussions on social media using NLP techniques to better understand the public's reactions to information and misinformation regarding COVID-19 during March of 2020. They built their sentiment analysis model using comments from the most popular COVID-19 subreddits using Reddit's API (8) and defined fifty discussion topics, which are groups of commonly co-occurring words, using Latent Dirichlet Allocation (LDA), a machine-learning-based natural language processing approach. With this study, they were able to identify patterns of public dialogue and suggest targeted interventions to combat misinformation. We use this study to guide the design of our work, as we plan to build our own sentiment analysis model and apply it to Reddit data, focus on specific categories of discussion related to different public health policies, and conduct significance testing on the results.

Additionally, Chakraborty et al. (29) performed sentiment analysis of Twitter data using deep learning classifiers, which are used to show how popularity affects the accuracy of information spread through social media, and conclude that fact checkers should be included in social media to prevent the spread of unnecessary information. Boon-Itt and Skunkan (44) used the Twitter API to collect tweets related to COVID-19, and after performing sentiment analysis and topic modeling on the data, concluded that analysis of Twitter data could explain public awareness and perception of the COVID-19 pandemic, while sentiment analysis and topic modeling can provide insight into discussion trends. Finally, Hung et al. (76) investigated COVID-19 sentiments by applying machine learning methods to analyze the sentiments of Twitter data, and the results help to clarify the public response.

These studies show us that social media data can contain meaningful information about people's sentiments regarding COVID-19, and the data can be interpreted using sentiment analysis models and significance testing. Since these related works have not specifically analyzed the response to state-level public health policies, we analyze the role state governors play in the dissemination of public health messaging during the COVID-19 pandemic.

1.3 Objective

The research questions that we hope to answer with this work are the following:

RQ1. How does public sentiment in response to COVID-19 policies compare between different states and policies?

RQ2. Does public sentiment parallel the spread of COVID-19?

RQ3. Is social media a good indicator of people's feelings towards policies?

We answer the above questions by analyzing public sentiment in response to COVID-19 safety measures in several US states, and we make the following major contributions:

1. Collect social media data regarding policies implemented by US governors posted on Twitter, Facebook, and Reddit using each respective platform's API.

2. Train and test a sentiment analysis model to calculate the sentiment scores for the social media natural language content.

3. Perform sentiment analyses on the social media natural language data.

4. Perform significance testing on the sentiment results and analyze the test results within the context of COVID-19 cases and deaths, policy, and politics.

With the results of the sentiment analyses, we run significance tests on aggregate sentiment scores for each policy as well as for intra-state and inter-state policies, meaning between states for the same category of policies and within states for different policies. We use COVID-19 cases and deaths, state political party distribution, and the policies themselves to contextualize the results and aid in the analysis of the significance test results. This work is important in order to understand how people in the US have responded to different public health policies and what factors may impact their responses. If we can determine how the public has responded to this pandemic and the ways in which government and public health officials have contributed to this response, society may be better equipped to combat future pandemics through improved public health messaging techniques.

Chapter 2

Design Rationale

2.1 Design

In order to answer our three research questions discussed in the previous chapter, we analyze the public sentiment in response to Facebook, Twitter, and Reddit posts related to state-level COVID-19 legislation and public health guidelines. We use Application Programming Interfaces (APIs) from Facebook (1), Twitter (12), and Reddit (8) to gather our data, and we conduct sentiment analyses on these data to determine the public's reaction to the governors' policies.

In order to determine from which social media posts to gather responses, we manually compile a list of COVID-19 guidelines issued by state governors in Arizona, California, Florida, Iowa, Michigan, Nevada, New York, Ohio, Pennsylvania, Texas, Washington, Wisconsin during March to October of 2020. We chose states based on the following criteria: population size to increase the possibility of finding social media discourse related to these states and political affiliation, such as states with historically consistent party distributions and swing states, since we wish to analyze how political affiliations of the governors and state populations may sway public opinion given how polarized the pandemic has become (37; 86; 26; 26). A state can be designated a swing state when it experiences "ideological polarization", which means the state experiences a greater ideological divide between parties. When the state has more moderate or independent voters, the competition between the Democratic and Republican populations intensifies, and thus political polarization occurs (90; 26). We only study the above 12 states given the time and scope limitations for our project.

We collected data from March to October of 2020 because that time frame encompasses the beginning of the pandemic when several important public health policies were put in place. These policies include shelter-in-place or similar orders, mask and face covering guidelines, and fall school reopening guidelines, which were all pivotal policies during the first eight months of the pandemic. All states we study implemented some form of these policies. Table 2.1 lists all the policies we studied in each state and when they were announced. For each of these policies, we manually search for social media posts from each governor about those guidelines and collect interaction and comment data from these posts.

Table 2.1: COVID-19 Policies Researched by State

State	Policy	Description	Date Announced
Arizona	Shelter-In-Place/Stay-At-Home	Executive order for individuals to limit time away from home except for essential activities (53).	March 30, 2020
	Fall School Reopening	Executive order that allow schools to offer options for distance learning and allow parents to decide between in-person and distance learning. Schools can offer in-person instruction based on Arizona Department of Health Services benchmarks (55).	June 24, 2020
	Masks/Face Coverings	Executive order allowing businesses and local governments to adopt policies regarding face coverings/masks (54).	June 17, 2020
California	Shelter-In-Place/Stay-At-Home	Executive order and Public Health order that directed all Californians to stay home except to go to an essential job or to shop for essential needs (84).	March 19, 2020
	Fall School Reopening	Guidance on school reopening that requires local health officer approval following their review of local epidemiological data including cases per 100,000 people, rate of test positivity, and local preparedness to support a health care surge, vulnerable populations, contact tracing, and testing (18).	July 17, 2020
	Masks/Face Coverings	Guidance which mandates that face coverings be worn state-wide in the circumstances and with certain exceptions outlined (25).	June 18, 2020
Florida	Shelter-In-Place/Stay-At-Home	Executive order that all persons shall limit their movements and personal interactions outside of their home to only those necessary to obtain or provide essential services or conduct essential activities (52).	March 28, 2020

	Fall School Reopening	Executive order that reopens brick and mortar schools with the full range of services for the students and families (51).	June 11, 2020
	Masks/Face Coverings	Guidance which encourages face masks in any setting where social distancing is not possible, but mask-wearing cannot be enforced (41).	October 7, 2020
Iowa	Shelter-In-Place/Stay-At-Home	There is no official guidance or executive order. There is a proclamation that closed a number of businesses and public venues until August 30, 2020 (21).	April 2, 2020
	Fall School Reopening	Executive order that schools must conduct at least half of their instruction in-person and schools may offer online programs as voluntary options for parents to select for their children, but districts must receive state approval if they want to move an entire building or district to online-only lessons (89).	July 17, 2020
	Masks/Face Coverings	Executive order that people must wear a face covering when indoors in public with certain exemptions (88).	March 17, 2020
Michigan	Shelter-In-Place/Stay-At-Home	Executive order to suspend activities that are not necessary to sustain or protect life which includes directing residents to remain at home or in their place of residence to the maximum extent feasible (102).	March 10, 2020
	Fall School Reopening	Executive order to reopen school in phases of the “Michigan Safe Start Plan”, which mandates that schools can only conduct in-person instruction if the state deems it safe to do so, otherwise schooling is done remotely (100).	June 30, 2020
	Masks/Face Coverings	Executive order to require individuals wear a face covering in indoor public spaces or crowded outdoor spaces, and that businesses can refuse entry or service to those who refuse to wear one (101).	July 10, 2020

Nevada	Shelter-In-Place/Stay-At-Home	Executive order for residents to stay at home and for non-essential businesses to close until April 30. However, residents are able to go outdoors in groups less than 10 and to keep 6 feet apart from others (96).	April 1, 2020
	Fall School Reopening	Executive order for schools to resume in-person teaching if they adhere to emergency directives, public health protocols, and Nevada Department of Education guidance throughout the 2020-21 school year (98).	June 24, 2020
	Masks/Face Coverings	Executive order for a mandatory face covering policy that requires people to wear a mask based on a recommendation by the Medical Advisory Team (97).	June 24, 2020
New York	Shelter-In-Place/Stay-At-Home	Executive order called "New York State ON PAUSE" requiring non-essential businesses to close and for people to limit movements outside of their home (23).	August 7, 2020
	Fall School Reopening	Guidance for schools in New York to reopen in the fall depending on their region's infection rate. School districts are required to submit plans to re-open and must comply with state health guidelines (22).	April 15, 2020
	Masks/Face Coverings	Executive order requiring New Yorkers to wear face coverings in public (83).	April 15, 2020
Ohio	Shelter-In-Place/Stay-At-Home	Executive order for people to limit their activity and practice social distancing, such as staying 6 feet apart when performing essential tasks or going outside (75).	March 22, 2020
	Fall School Reopening	No executive order. The governor encouraged schools to reopen for in-person instruction, but ultimately let the schools decide when they would do so (27).	June 3, 2020

	Masks/Face Coverings	Executive order for a statewide mask mandate to take effect on July 23, 2020 (24).	April 1, 2020
Pennsylvania	Shelter-In-Place/Stay-At-Home	Executive order for individuals to remain at home unless performing essential activities, in addition to being allowed to go outdoors with social distancing (103).	April 1, 2020
	Fall School Reopening	Pennsylvania Department of Education released guidelines for when schools could reopen for in-person instruction based on health statistics in each county (28).	August 10, 2020
	Masks/Face Coverings	Executive order for face coverings to be worn at all times with some exceptions, such as being outdoors or having situations where it may not be ideal (72).	July 1, 2020
Texas	Shelter-In-Place/Stay-At-Home	Executive order to practice social distancing (39).	August 19, 2020
	Fall School Reopening	Guidance for local school districts to have the discretion over when and how to start the school year (99).	August 19, 2020
	Masks/Face Coverings	Executive order for face coverings to be worn in public settings (38).	July 2, 2020
Washington	Shelter-In-Place/Stay-At-Home	Executive order called “Stay home, stay healthy” issued for all residents to limit their movements beyond essential needs, and for only essential businesses to remain open (67).	March 24, 2020
	Fall School Reopening	Guidance for school reopening based on public health science and data provided by the State Department of Health (77).	June 11, 2020
	Masks/Face Coverings	Executive order for a statewide mask mandate to go into effect on June 26, 2020 (66).	June 23, 2020
Wisconsin	Shelter-In-Place/Stay-At-Home	Executive order for Wisconsin residents to only perform essential tasks. Businesses can only open for essential duties with some exceptions (20).	March 24, 2020

	Fall School Reopening	Guidance for school reopening included a document published by the Wisconsin Department of Public Instruction for school districts and leaders to plan for a safe reopening of schools (19).	June 22, 2020
	Masks/Face Coverings	Executive order issued on July 30, 2020 for everyone to wear a mask in public (59).	July 30, 2020

2.1.1 Data Sources

Based on survey data from the COVID 50 States Survey (50) that was performed one week at a time between April and August of 2020, Figure 2.1 shows that the top three news sources that people utilized to learn about health guidelines and news related to COVID-19 policies were local television, friends and family, and network television. Social media was also one of the highest methods that users cited for getting information related to COVID-19 amongst all of the states evaluated. We decided to study social media data overall because it provides extensive historical data from the past year regarding public discourse, and it is also a useful tool for government officials to spread information, such as COVID-19 safety measures. Furthermore, Facebook was shown to be the most popular social media source that people used to get COVID-19 related data. The survey also showed that 52 percent of respondents obtained COVID-19-related news from Facebook within 24 hours of when they filled out the given survey, with 14 percent and 5 percent having obtained such from Twitter and Reddit, respectively.

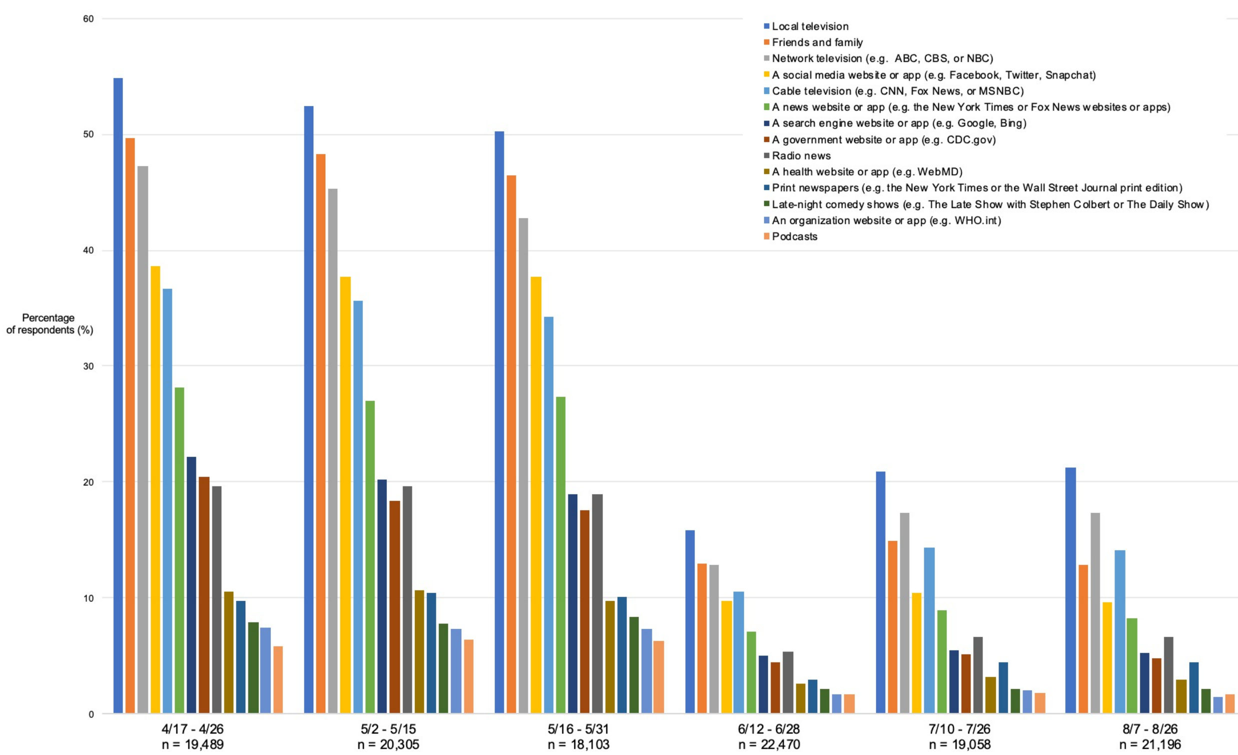


Figure 2.1: Distribution of COVID-19 Information Sources Used Nationally (50)

2.1.2 Social Media Platforms

We maximize the amount of user sentiment data collected by using the most popular platforms amongst users. Based on the COVID 50 States Survey (50), we chose to collect data from Facebook, Twitter, and Reddit since these sources were among the top social media platforms used to obtain COVID-19 related information during March to August of 2020 as shown in Figure 2.2. Facebook and Twitter were among the top three, and although YouTube, Instagram, and Snapchat were higher in ranking than Reddit, our goal is to collect text-based data, which is not easily gathered from these image- and video-based sources. Overall, social media platforms provide users the opportunity to engage in conversation on a public level, which in turn provides us with valuable data for our research.

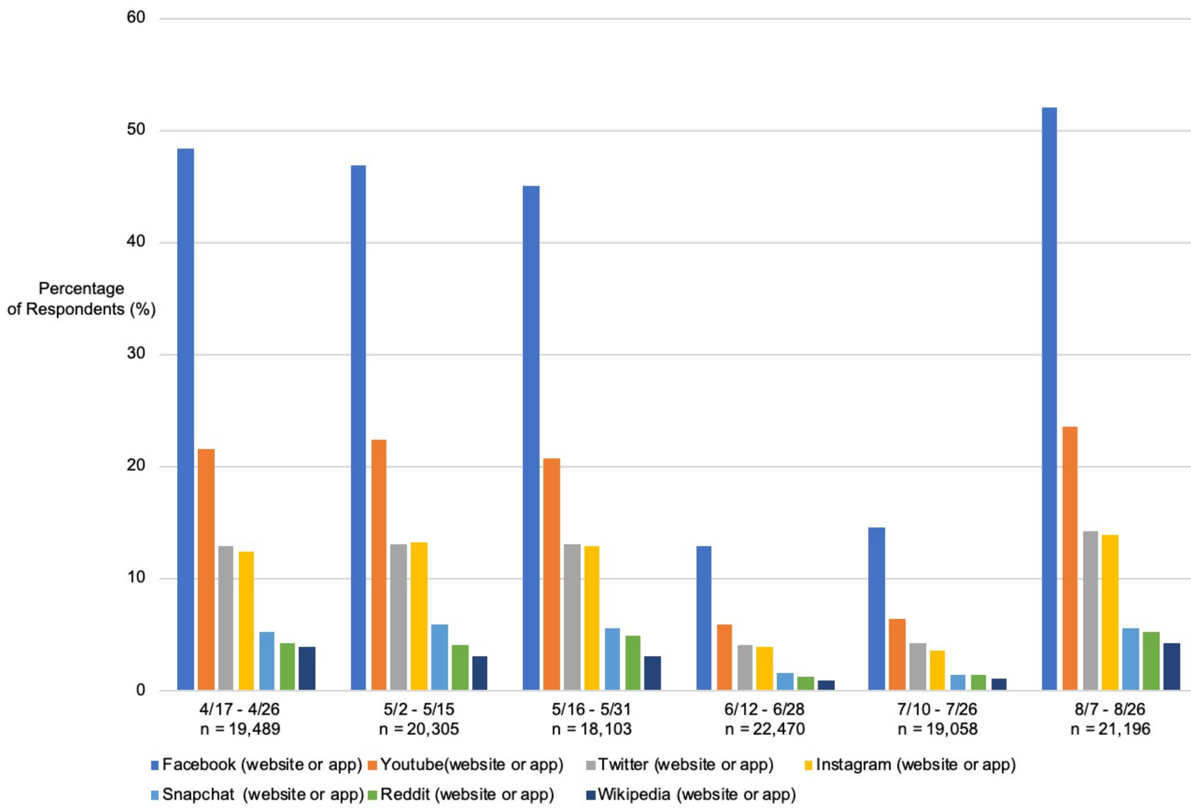


Figure 2.2: Distribution of Social Media Usage for COVID-19 Information Nationally (50)

Facebook has a high level of user engagement, with more than 1.84 billion active daily users (80). It allows users to express themselves through reactions to a post, such as “like”, “love”, “sad”, and “angry”, which are useful for our sentiment analysis (31). After searching for state governors and their policies and guidelines related to COVID-19, we gather the total reactions of a Facebook post using CrowdTangle (1), which is one of Facebook’s APIs that tracks and displays public user content and engagement.

There are 192 million active users on Twitter (73). Users can share their thoughts through “tweets”, which are Twitter social media posts, and other users can respond through replies (35). We are able to retrieve replies to governor tweets using the Twitter API (12). Users can also show approval of and share tweets through “retweets” and “likes”, which are statistics that can aid in sentiment analysis (12).

Our last data source is Reddit (33), which is composed of "subreddits". Subreddits are small communities within the platform in which users can engage in conversation by posting news articles or their own thoughts. They can "upvote" or "downvote" comments and posts to show agreement or disagreement with the commenter or poster. Using the Reddit API (8), we collect data from five subreddits, which have a collective membership of over 58 million users.

We collect Twitter tweets related to COVID-19 safety measures posted by state governors similarly to how we chose the Facebook posts. Starting from the Twitter and Facebook accounts of a governor, we retrieve the posts containing the policies we identified, and then gather the responses and reactions. Our Reddit data collection process is similar, however, instead of searching for a state governor, we collect comment discussions on relevant posts from selected subreddits such as r/Coronavirus, r/COVID-19, r/News, r/Politics, and r/Science, since most governors do not have official Reddit accounts like they do on Facebook and Twitter. Given that CrowdTangle does not allow users to collect textual content from Facebook comments, we only input our collected Twitter and Reddit data to the sentiment analysis model.

2.1.3 Rationale and Assumptions

We had to make the following assumptions about circumstances related to our research given that there are so many factors that impact social media data collection and information related to the pandemic. While we cannot prevent or accommodate for every factor, taking them into account provides context and could provide researchers more topics to explore.

Data Collection Timeline

We limited our data collection to the time period between March to October of 2020 due to the time constraint of this project. Since the COVID-19 pandemic is ongoing and concurrent with this work, we must set a concrete timeline and choose specific policies to study. Gathering data is time consuming and takes significant computing power. Therefore, in order to find meaningful results within the timeline of this project, we limited our focus to three viable social media platforms and chose to analyze state guidelines on fall school reopening, mask guidelines, and shelter-in-place order which occurred during March to October of 2020. This research can be extended to a longer time period to study more policies throughout the pandemic, but we had to be realistic with our project scope.

Geographic Location of Users

Since we are unable to retrieve geographic location data for all the Facebook, Twitter, and Reddit users interacting with governors' posts, we have to assume that most users interacting with these posts are from the corresponding states and are thus impacted by those policies. We make this assumption because our aim is to study the public sentiments of the people in each state that are directly impacted by the policies implemented by state governors and not people from other places, since people living in each state are the ones mostly contributing to the spread of COVID-19 in their state. While we cannot assure that this assumption is true, we acknowledge that this limitation exists.

Social Media Post Sentiment Meaning

We assume that user commentary on social media posts reflect their true opinion of the post content, and likewise their view of their state's legislation. We make this assumption because our research relies on social media data to determine the public sentiment in response to policies. For our Reddit and Twitter data, we analyze average sentiment score for social media posts, so if there is a positive sentiment score, we interpret that as users approving of the content of the post on average, and we assume the opposite if there is a negative sentiment score. On Facebook, this means that interactions such as "like", "love", and "care" mean to approve of the post content whereas "sad" and "angry" mean the opposite.

Secondary User Interaction

We assume that secondary users who interact with the primary Reddit comments and Twitter replies, such as by liking and retweeting on Twitter, or upvoting and downvoting on Reddit, are reflecting their opinion of the content of the post, either in agreement or disagreement. This assumption is critical in the creation of our weighted Reddit and Twitter datasets, in which we amplify sentiment scores of posts based on how many likes and retweets on Twitter it receives and upvotes on Reddit it receives. For example, if a Reddit post receives 20 downvotes and the sentiment score of the post is positive, then we add 20 data points of the original sentiment score with negative polarity to the dataset since those 20 downvotes indicate disagreement with the post content, effectively incorporating the disagreement with this post content from other users to the dataset.

2.1.4 Factors

There are several factors and platform-specific limitations that may affect our results that we cannot eliminate based on the context of our project. Given the nature of social media data research, these factors and limitations cannot be accounted for since these data are not available for users of these platforms. Table 2.2 summarizes data collected by the Pew Research Center in 2021 (47) from a study about the demographics of social media usage by US adults.

User Age and Sex

Table 2.2 shows that 36 percent of US adults between the ages of 18 and 29 use Reddit, 42 percent of US adults between the ages of 18 and 29 use Twitter, and 77 percent of adults aged between 30 and 49 use Facebook. These age ranges constitute the largest group on each platform. Additionally, more US adult men use Twitter and Reddit than do US adult women, whereas more US adult women use Facebook than do US adult men. Thus, all three social media platforms vary in their user base, which may impact the results of this study as we are unable to determine the distribution of the sex and age of the users in our dataset.

User Education Level

According to Table 2.2, 73 percent of US adults who are college graduates use Facebook, 33 percent of US adults who are college graduates use Twitter, and 26 percent of US adults who are college graduates use Reddit (47). The other categories, "high school or less" and "some college", contain less users for each of the platforms than does the "college graduates"

Table 2.2: Social Media Usage Demographics (47)

% of U.S. adults in each demographic group who say they ever use ...

	Facebook	Twitter	Reddit
Total	69%	23%	18%
Men	61%	25%	23%
Women	77%	22%	12%
Ages 18-29	70%	42%	36%
30-49	77%	27%	22%
50-64	73%	18%	10%
65+	50%	7%	3%
White	67%	22%	17%
Black	74%	29%	17%
Hispanic	72%	23%	14%
Less than $30K	70%	12%	10%
$30K-$49,999	76%	29%	17%
$50K-$74,999	61%	22%	20%
More than $75K	70%	34%	26%
High school or less	64%	14%	9%
Some college	71%	26%	20%
College graduate	73%	33%	26%
Urban	70%	27%	18%
Suburban	70%	23%	21%
Rural	67%	18%	10%

category. Thus, US adults who are college graduates use each platform more than do US adults with either some college education, high school, or less. This means that our datasets may contain more content from college graduates than from other education levels given the higher proportions in each platform.

User Income Level

Table 2.2 shows that US adults whose income is between $30K and $49,999K use Facebook the most (76 percent) compared to the other income levels. Also, US adults whose income is more than $75K use Twitter and Reddit the most (34 and 26 percent, respectively) compared to the other income levels. Given this distribution, we may not be getting the full perspective of people in each income level in our dataset.

User Race and Ethnicity

Table 2.2 shows that US Black adults use Facebook and Twitter more (74 and 29 percent, respectively) than do White and Hispanic US adults, whereas US Black and White adults use Reddit more (both 17 percent) than do US Hispanic adults. Again, since we have no way to determine the race and ethnicity of users in our datasets, these uneven distributions may impact our dataset.

Chapter 3

Technologies and Data Sources

3.1 Technologies

We used the following tools for our project:

- Data Collection
  - Twitter API (12)
  - Twarc API (Twitter API Wrapper) (34)
  - Reddit API (8)
  - Pushshift API (Reddit API Wrapper) (6)
  - Facebook's CrowdTangle API (1)
  - Python programming language (7)
- Sentiment Analysis Model
  - Python programming language (7)
  - Google Colaboratory for version control and code base sharing (4)
  - Natural Language Toolkit (NLTK) package for Python (5)
- Significance Testing
  - Python programming language (7)
  - Google Colaboratory for version control and code base sharing (4)
  - statsmodels package for Python (68)

3.2 Data Sources

Here is a list of the data sources we used for our analysis and system:

- Coronavirus Tweets Dataset for sentiment analysis model training (70)
- Facebook data from the CrowdTangle API (1)
- Twitter data from Coronavirus Tweets Dataset (70) and Twitter API (12)
- Reddit data from their API (8)
- The COVID 50 States Surveys data (50)
- COVID-19 confirmed cases and deaths US states provided by Johns Hopkins University (56)

Chapter 4

Methodology

4.1 Data Collection

4.1.1 Facebook Data

We gathered Facebook data using CrowdTangle (1), Facebook's API that tracks public content. Since we are analyzing US governors' Facebook posts, we manually searched for verified state governors' Facebook profiles and posts relating to target policies to retrieve the total number of interactions that each post received. CrowdTangle does not allow users to access textual data from comments to posts, so we only used the Facebook interaction data, such as likes on posts, alongside the sentiment analysis of the Twitter and Reddit data. Facebook allows users to use the following interactions on posts: "like", "love", "haha", "wow", "sad", "angry", and "care" (31). We consider "like", "love", and "care" to be positive interactions and "sad" and "angry" to be negative interactions. The "haha" and "wow" interactions are more difficult to interpret, so we do not group them into either the positive or negative category since we cannot be sure what users mean when they use these interactions on a given post.

4.1.2 Twitter Data

Similarly to the Facebook data, we manually searched for verified state governors' Twitter profiles and tweets relating to their statewide COVID-19 policies and guidelines. Twitter's API (12) does not support historical data collection, so we used a dataset created by Lamsal (71) that contains more than 400 files with tweet IDs collected since January of 2020, totaling to more than 1.2 billion tweets, to collect the replies to governors' tweets. This dataset is available on IEEE Dataport and was collected using popular COVID-19 hashtags and keywords. Lamsal performed sentiment analysis on the data they collected and published the sentiment scores along with the tweet IDs (71).

Using the tweet IDs from the preexisting dataset and the Twitter API, we hydrated the tweets from the timelines of the policies in each state. Tweet hydrating means collecting the full tweet data by inputting the tweet ID to the Twitter API. We manually searched for tweets related to the target policies posted by governors from each state we wished to study, and some governors posted several tweets in reply to their own tweet, which is a common practice on Twitter since the platform limits the length of tweets. Of the tweets available in the dataset, we hydrated 6.95 million tweets from the period of March to October corresponding to the timelines when our target policies were posted to Twitter, and we found 4,252 tweets in reply to our list of governor tweets that we wished to study. We searched for replies within four weeks of the posting date of each governor's tweet. For the policies for which we collected multiple governor tweets within the same tweet thread, the timeline in which we searched for replies in the preexisting dataset ranged from the oldest tweet to four weeks after the newest tweet related to a given policy.

In order to account for other user interaction with these replies, we used the likes and retweets of the replies to the governor tweets to create a weighted dataset. For each like and retweet a tweet received, we added the original tweet's sentiment to the dataset to amplify the sentiment of the replies, considering that other users like and/or retweet a tweet if they agree with its content. We gathered the number of likes and retweets to each tweet using the tweet IDs and twarc, a Python library and command line tool used to access Twitter API content (34).

4.1.3 Reddit Data

Unlike Twitter, Reddit allows access to historical data, so we were able to collect Reddit data ourselves. We used the Reddit API (8) and Pushshift API (6), the latter being a wrapper for the Reddit API that allows users to more easily find posts in specific time ranges, to collect data related to our target governor policies. We extracted posts from five subreddits: r/Coronavirus, r/news, r/science, r/COVID19, and r/politics. We further filtered for posts containing commentary on the state-specific governor policies, and gathered 175 relevant posts in total. Using the post IDs, we gathered the comment text and upvotes for each post using the Reddit API. From all posts, we collected 7,094 comments in total.

We created a weighted version of the Reddit dataset using the upvotes, similarly to how we constructed the Twitter weighted dataset. Reddit is different from Twitter in that users can also downvote Reddit content, implying disagreement with the post content. Given this extra functionality, we multiplied the sentiment by the polarity of the upvotes to generate the score that aligns with the polarity of the upvotes value, with negative upvotes meaning users downvoted the post. For each upvote, we added that newly calculated sentiment value to the dataset, effectively amplifying the scores, both negative and positive, based on the level of user interaction. Once we gathered all the relevant data, we used our sentiment analysis model to generate sentiment scores for the comments of each post.

4.2 Sentiment Analysis Model

We built the sentiment analysis model using a natural language processing package for Python called Natural Language Toolkit (NLTK) (5). We used Lamsal's dataset (71) to train and test our model since it contains social media content, similarly to Reddit data, and it is already labeled with sentiment scores. After we trained our model, we tested it with several classifiers to pick the one with the highest accuracy. Finally, we applied our sentiment analysis model to our Reddit data to generate sentiment scores.

4.2.1 Data Pre-Processing

We used our hydrated tweet dataset created using Lamsal's dataset (71) since it contains the natural language text from each tweet and the labeled sentiment scores to train and test our model. First, we grouped the hydrated Twitter data into three categories based on the sentiment score, which ranges from -1.0 to 1.0, with negative sentiment being represented by scores less than 0, positive being represented by scores greater than 0, and neutral being represented by a score of 0. Using NLTK library functions, we then calculated the percentage of positive, neutral, and negative sentiments in the text. The raw sentiment score is the difference between the positive and negative proportions. After that, we tokenized the tweet data by breaking sentences into smaller units called tokens. Next, we removed the noise from the dataset. Noise refers to the characters or words that may exist in a sentence that do not add any sentiment meaning. Moreover, noise is specific to each context, which means that certain characters or words may be relevant in one context but irrelevant in another. In our project, noise includes hyperlinks, numbers, punctuation, special characters, and text commonly found in social media data that are not actual words, such as "RT", which means "Retweet" on Twitter. We removed noise using regular expressions and then further processed the data by removing stopwords. Stopwords are words commonly used in sentences that do not contribute to sentiment, such as "and", "or", "is", and "this". Additionally, Hung et al. (76) suggest adding coronavirus-related terms, such "covid19", "corona", and "coronavirus" to the stopwords, since these do not contribute to sentiment. Finally, we normalized our dataset with lemmatization, which means to transform each word back to its dictionary form, such as "better" to "good" and "walking" to "walk".

4.2.2 Training and Testing

We split the Twitter dataset into 70 percent for training and 30 percent for testing and use the Naive Bayes and Logistic Regression Classifiers to determine the appropriate size for our training and testing data. We found that 300,000 is the ideal size of training and testing data input. Then we tested our model with ten different classifiers to determine which classifier could achieve the highest accuracy. After testing with multiple classifiers as shown in Table 4.1, the Random Forest Classifier provided by the NLTK package gave us the highest accuracy, so we chose this classifier for our model and applied it to our Reddit dataset. We do not apply the model to the Twitter dataset since we already have sentiment scores provided by Lamsal (71), and we do not apply the model to the Facebook data since it does not contain natural language content.

4.3 Statistical Analysis

As previously mentioned, we generated unweighted and weighted datasets for both Reddit and Twitter data based on upvotes, likes, and retweets. For Twitter, we performed significance testing on four different versions of the dataset; unweighted, weighted by likes, weighted by retweets, and weighted by a combination of likes and retweets. For Reddit, we tested on two datasets; weighted by upvotes and unweighted. We conducted significance testing on all six datasets in order to analyze the effect weighting has on each platform for each test.

We used the Python statsmodels package (68) to run significance tests on the sentiment score sample mean for inter-state

Table 4.1: Classifier Testing and Accuracy of Sentiment Analysis Model

Classifier	Accuracy
Naive Bayes	75.51%
Bernoulli NB	80.47%
Complement NB	76.89%
Multinomial NB	77.98%
K-Neighbors	80.04%
Decision Tree	90.04%
Random Forest	**91.44%**
Logistic Regression	89.77%
MLP Classifier	91.23%
AdaBoost Classifier	68.32%

and intra-state policies, meaning the same policies between different states and different policies within the same state. We ran one-sided, two-sample z- and t-tests based on the sample sizes of the input data. We ran each test twice to test both sides of the alternative hypothesis. We performed 1,080 significance tests across all six datasets and all combinations of state and policy. Out of those 1,080 tests, we had 250 statistically significant results, meaning the resulting p-value of the significance test was less than 0.05. We also calculate the average sentiment scores across all the states for each policy and perform significance testing on those data. We utilize the weighted datasets from Reddit and Twitter as these provide insight into how more users are interacting with the replies to the governor posts.

Chapter 5

Results and Analysis

5.1 Introduction

The results of our significance testing are discussed and analyzed in this chapter. We calculated the average sentiment across all the states for each policy in order to get a broad view of how users have reacted to each policy and conduct significance tests on those data to compare the reactions for each type of policy. We used the Reddit weighted dataset and Twitter combined weighted dataset, which account for interactions from both the post replies and other interacting users on each platform. Sentiment scores range from -1.0 to 1.0, with -1.0 indicating the most negative sentiment and 1.0 indicating the most positive sentiment. We also conducted intra- and inter-state significance tests to statistically compare user sentiment between states and policies.

5.2 Aggregate Public Sentiment

Using a combination of our Reddit and Twitter weighted data, we ran significance tests on the mean sentiments for each policy across all states. The sample mean sentiment in response to mask policies is 0.131, to school policies is 0.122, and to shelter-in-place policies is 0.119. The average sentiment in response to mask policies is statistically significantly greater than that of shelter-in-place policies ($p\text{-value}<0.05$) and fall school reopening policies ($p\text{-value}<0.05$). Since the policies we studied vary in terms of severity and who enforces them, such as mask policies that mandate masks across the state compared to mask policies that allow counties to make the decision, these data do not indicate any public sentiment towards the specific details of the policy. Rather, this indicates that people had on average a more positive reaction to the mask policies in their state than they did with the school reopening and shelter-in-place policies. It is important to note that people's reaction to each of the aforementioned policies is not necessarily due to the specifics of each, given that our testing strategy was to group them together. These results may suggest that perhaps people are more willing to comply with mask mandates than they are with state and school closures, which occurred during the more dire moments of the pandemic throughout the country.

5.3 Intra- and Inter-State Significance Testing

We ran 1,080 intra- and inter-state significance tests across all combinations of state and policy and within all six datasets, which contain Reddit and Twitter weighted and unweighted data. In an effort to gather more user reactions to governor policies, we use the Reddit weighted and Twitter combined datasets for our analysis. Out of the 250 significant test results, we ran 224 inter-state and 26 intra-state tests. Of the inter-state tests we ran on the weighted Twitter and Reddit datasets, we identified nine that had the same results from both Reddit and Twitter, meaning that the test run for the same policy and state combination resulted in the same conclusion on both platforms. The inter-state significant test results from the weighted Twitter and Reddit datasets with the same outcomes across platforms as well as the interaction data for the corresponding governor posts on Facebook are summarized in the Table 5.1. As was mentioned before, we consider "like", "love", and "care" to be positive interactions and "sad" and "angry" to be negative interactions. The "haha" and "wow" interactions are more difficult to interpret, so they have been excluded from the dataset. Thus, the two columns in Table 5.1 with the percentage of positive and negative interactions for each post do not add up to 100 percent across the rows since we do not include the "haha" and "wow" interactions.

Amongst the intra-state tests, we identified one out of the 15 tests run on the weighted datasets that had the same outcome from both Reddit and Twitter, which means that the rest run for two different policies within the same state resulted in the same conclusion on both platforms. Table 5.2 lists the intra-state significant test results for the weighted Twitter and Reddit datasets as well as the interaction data for the corresponding governor posts on Facebook. Entries with "N/A" in the Facebook columns indicate that we were unable to find a Facebook post from that specific governor about the given policy. The entries denoted with "*" indicate that the tests resulted in the same outcome across both Twitter and Reddit.

5.3.1 Inter-State Test Result Analysis

In this section, we will analyze the results listed in Table 5.1 in the context of each state's COVID-19 cases and deaths, which are shown in Figures 5.1 and 5.2, and distribution of political party affiliation, which are listed in Table 5.3.

Out of the nine inter-state significant test results, six of those involved fall school reopening policies. The average sentiment in response to the fall school reopening policies in Arizona, California, Florida, Iowa, Michigan, and New York were statistically significantly higher ($p\text{-value} < 0.05$) than that of Ohio. Based on the sample means listed in Table 5.1, Ohio had a negative sentiment on Reddit and Twitter, California had positive sentiments on both platforms, and Florida, Iowa, Michigan, and New York had positive sentiments on Reddit and negative sentiments on Twitter. Higher average sentiments in response to a policy indicate that the public is more supportive of that policy. To further investigate which factors may lead to these results, we have researched the details of the policies, the COVID-19 cases and deaths, and the political affiliations in each state. The policies studied for each state are listed in Table 2.1. The governors in Arizona, California, Michigan, and New York implemented policies that only allowed schools to open in-person if the counties met certain public health guidelines instituted by the states' public health departments, otherwise schools had to conduct remote instruction (55; 18; 100; 22). Florida's governor ordered all schools to reopen for in-person instruction in the fall, Iowa's governor ordered all schools to

Table 5.1: Inter-State Significant Test Results and Facebook Interaction Data

Policy	State	Reddit Sample Size	Reddit Sample Mean	Twitter Sample Sizes	Twitter Sample Means	Alternative Hypothesis	Reddit p-value	Twitter p-value	Facebook % Positive Interactions (like, love, care)	Facebook % Negative Interactions (sad, angry)
Fall School Reopening	Arizona	349	0.375731	33	-0.000336	µ AZ > µ OH	3.94E-24	3.57E-04	67.36	27.78
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Fall School Reopening	California	81	0.163126	5090	0.315874	µ CA > µ OH	2.19E-05	3.26E-282	97.31	2.00
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Fall School Reopening	Florida	1065	0.092576	792	-0.030193	µ FL > µ OH	9.70E-11	6.24E-08	95.37	3.62
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Fall School Reopening	Iowa	34	0.4391004	335	-0.050662	µ IA > µ OH	9.42E-07	9.29E-05	66.86	29.98
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Fall School Reopening	Michigan	82	0.135757	3765	-0.041069	µ MI > µ OH	7.59E-05	3.73E-25	97.74	0.83
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Fall School Reopening	New York	1734	0.246463	1911	-0.053007	µ NY > µ OH	8.07E-20	1.00E-10	79.32	16.31
	Ohio	194	-0.233408	411	-0.123398				92.73	5.54
Masks	California	11887	0.20479	6939	0.072713	µ CA > µ MI	3.41E-16	0.00E+00	92.93	1.59
	Michigan	8347	0.128173	3674	-0.095808				95.22	3.29
Masks	Michigan	8347	0.128173	3674	-0.095808	µ MI < µ OH	1.32E-20	7.11E-177	95.22	3.29
	Ohio	5364	0.229566	1201	0.057365				79.23	17.55
Masks	Michigan	8347	0.128173	3674	-0.095808	µ MI < µ PA	4.74E-31	6.46E-10	95.22	3.29
	Pennsylvania	1108	0.346921	238	-0.034908				74.04	7.12

offer at least half of their instruction in-person and online options, and Ohio's governor encouraged schools to reopen for in-person instruction, but ultimately let schools decide (51; 89; 27). Since these policies all vary, the specifics do not seem to be a factor that would explain our sentiment results.

When comparing the COVID-19 cases and deaths in each of the aforementioned states with those of Ohio during the times in which each states' policies were implemented, Arizona, California, Florida, Iowa, Michigan, and New York were experiencing more cases per one million people than was Ohio, as is seen in Figures 5.1 and 5.2, plots a-g, which indicates that those states had a more intense spread of the virus during that period than did Ohio. This difference in COVID-19 cases may explain why the sentiments differ; since all the states seem to have higher rate of case increase than Ohio does, people in Ohio may be more negative towards polices if they think there is no need for them.

Ohio has the greatest proportion of adults who identify as Republican or who lean Republican, as seen in Table 5.3. This difference may be a factor that influences the difference in sentiment between Ohio and the other five states. It is possible there are political differences that influence opinion regarding public health policies. However, we recognize the limitations of this study. First, these distributions may have changed, since the latest data is from 2014. Additionally, Arizona, Florida, Iowa, and Ohio have Republican governors whereas California, New York, and Michigan have Democratic governors. With the limited number of states involved in this study and the lack of common theme amongst governor party affiliations, more in-depth studies need to be done to comprehensively explain the differences in sentiment.

We also compare the Facebook interactions of the governors' posts regarding their policies with the Reddit and Twitter results, which are also listed in Table 5.1. On Facebook, the posts from California, Florida, and Michigan governors had larger proportions of positive interactions than did the post from Ohio's governor, and the posts from Arizona, Iowa, and New

York governors had smaller proportions of positive interactions than did the post from Ohio's governor. Each of the six states' posts had varying proportions of positive and negative interactions when compared to Ohio's post interactions on Facebook, so there does not seem to be a parallel in Facebook sentiment with Reddit and Twitter sentiment. This may indicate that there are differences in the demographics of users on these platforms that impacts the sentiment instead. In Chapter 2, Design Rationale, we discussed the various factors that may impact the results of our study based on the Pew Research Center study (47) that summarizes social media usage in US adults. Table 2.2 shows that Twitter and Reddit have larger proportions of US adults aged 18-29 than does Facebook, and Facebook has more US adults aged 30-49 using the platform. Additionally, the platforms differ in user income level; more US adults whose income is between \$30K and \$49,999K compared to other income levels use Facebook while more US adults whose income is more than \$75K also compared to other income levels use Reddit and Twitter. These data may highlight how these demographics play a role in the public sentiment in response to these policies, since there are differences in the demographics of users who are reacting to these posts. More research should be done to study if there are any correlations between these distributions and user sentiments across different social media platforms.

We researched Ohio's COVID-19 pandemic response to find out what other factors could possibly lead to Ohioans having lower average sentiments in comparison to these other states. Based on reporting from NBC News in May of 2020 (95), Ohioans were extremely divided on their view of the state's handling of the pandemic, and many were particularly angry with Dr. Amy Acton, the director of Ohio's Department of Health, who worked alongside Governor Mike DeWine to fight the spread of coronavirus. Acton has become the target of protests, threats, and overall hate as people in the state seemed to believe that the state was overreacting to the pandemic given all the orders implemented (95). Acton is also the first woman to hold the position of director of the Department of Health in Ohio. Christopher Devine, an assistant professor of political science at the University of Dayton, stated "The fact is many of these restrictions are being announced and enacted by a woman in power, in a state that has put very few women in major leadership roles", implying that people are letting their prejudices impact their responses to COVID-19 public health guidelines (95). The article discusses that Ohio was more aggressive in its COVID-19 response than were the White House and other similar states (95). Finally, Ohio was considered a swing state in 2020 (90; 26), which provides context for our sentiment results. Ohio may have been experiencing intense political polarization and therefore a more negative response to public health policies than were the other states mentioned before. While we are not suggesting in this study whether these factors directly account for the differences in sentiment, we discuss them here as they provide context for these results and can be explored in future work.

Furthermore, of the nine inter-state tests, three involved mask policies. We found that the sentiments in response to the mask policies in California, Ohio, and Pennsylvania were statistically significantly higher than that of Michigan. Based on the sample means listed in Table 5.1, Michigan and Pennsylvania had negative sentiments on Twitter and positive sentiments on Reddit whereas California and Ohio had positive sentiments on both platforms. As seen in Table 2.1, the governors of California, Michigan, Pennsylvania, and Ohio all implemented mask mandates that required all people in their state to wear a face covering in most places outside their home, such as indoor public spaces and crowded outdoor spaces (25; 101; 72; 24).

Since there is no difference between Michigan's policy and the other three state's policies, the specific details of the policies do not seem to be a factor that would explain our sentiment results.

The COVID-19 cases and deaths during the times that these policies were implemented in each state is shown in Figure 5.1 plots h-k. The COVID-19 cases were similar across all these states during each time period, however, the rate of spread varies. California's and Ohio's positive case counts seem to be increasing at a higher rate than were Michigan's, and Pennsylvania's rate of positive case increase seems more similar to that of Michigan. Since only California's and Ohio's case increase rate differs and Pennsylvania's does not when compared to that of Michigan, this does not seem to be a factor in explaining the differences in sentiment.

California, Pennsylvania, and Michigan all have Democratic governors whereas Ohio has a Republican governor, as is listed in Table 5.3. Table 5.3 also shows that California, Pennsylvania, and Michigan have higher proportions of adults who identify as Democrat or who lean Democrat than those who identify as Republican or who lean Republican within each state, and in Ohio, there is a higher proportion of adults who identify as Republican or who lean Republican than those who identify as Democrat or who lean Democrat within the state. Since there does not seem to be a common trend for this factor when comparing these four states, political affiliation distributions and governor party affiliation may not be a factor that explains the sentiment differences between Michigan and these three states. Again, the data for state political distribution may be outdated as it is from 2014 and the distribution may have changed drastically, but from the data that is available, it seems it may not be a factor that would explain these sentiment results.

On Facebook, the posts from California, Ohio, and Pennsylvania governors all had smaller proportions of positive interactions than did the post from Michigan's governor. The Facebook posts from the Ohio and Pennsylvania governors had larger proportions of negative interactions than did the post from the Michigan governor, which follows with the Reddit and Twitter test results. However, the Facebook posts from the California governor had smaller proportion of negative interactions than did the post from Michigan's governor. Thus, there does not seem to be a parallel in Facebook sentiment with Reddit and Twitter sentiment. Similarly to the fall school reopening tests, this may indicate a difference in demographics of the social media platforms that yield different sentiment results.

Since the above factors are not all common themes when comparing Ohio, Pennsylvania, and California with Michigan, we analyze what other factors may differentiate the states. Ohio, Pennsylvania, and Michigan were considered as potential swing states in 2020, and California was not. Our test results may indicate that there was more controversy and polarization occurring around the topic of masks in Michigan than there was in California, Ohio, and Pennsylvania (37; 86; 90; 26). According to reporting from the New York Times and Detroit Free Press (82; 45), Michigan did experience political polarization in 2020, and the governor was criticized by many in the state, in addition to the President of the United States, for the policies she implemented to stop the spread of COVID-19. The New York Times reports that in April of 2020, thousands of people protested Governor Gretchen Whitmer's executive orders related to COVID-19 at Michigan's State Capitol (82). In another case, according to the New York Times (82), six individuals were charged with conspiracy involving plans to kidnap and harm Governor Whitmer and other officials in order to overthrow Michigan's government in 2020. Finally, in May of 2020, two people were arrested in Flint, Michigan, after fatally shooting a store security guard due to a dispute over a customer not wearing a mask in accordance with the store's policy (79). These reports may indicate that Michigan was experiencing severe political polarization that lead to lower sentiment scores in response to public health policies.

Our results indicate that Ohio and Michigan, which were both swing states in 2020 that experienced notable political polarization, were states that had lower sentiments regarding fall school reopening policies and masks, respectively, when compared to several other states. These results provide a motivation to study what factors may lead to the differences in sentiment regarding public health policies and whether there exist correlations among political polarization and response to public health policies.

5.3.2 Intra-State Test Result Analysis

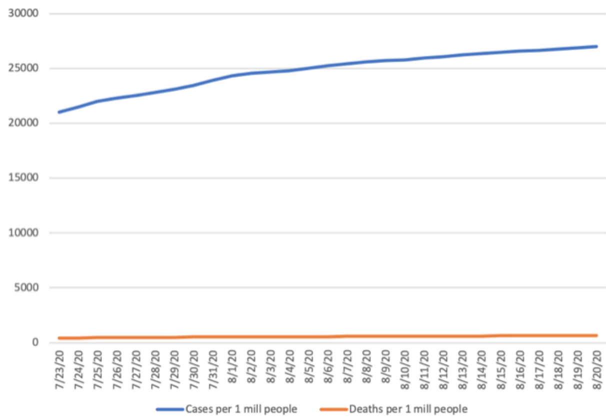
In order to analyze the intra-state test results, we group the states into swing states and those that are not. Amongst the intra-state test results listed in Table 5.2, the following states were considered potential swing states prior to the 2020 presidential election based on the aforementioned criteria: Arizona, Florida, Iowa, Michigan, Nevada, Ohio, and Pennsylvania (26). The rest of the states in Table 5.2, California, New York, and Washington, were not considered swing states and are consistently Democratic-leaning states. Considering we had more swing states with statistically significant differences in public sentiment across state-wide policies than we did non-swing states, perhaps the nature of the political party distributions in these states factors into how people respond to policies. Since swing states have a more even distribution of party representation, and therefore a greater divide in opinions, these data suggest that there was indeed a divide in the response to certain policies over the course of the pandemic in swing states more so than in non-swing states, which may be attributed in part to the partisan response to the virus in the US (86; 37; 46). These polarized responses to state-level policies may have played a role in each state's spread of COVID-19 given that the public was often exposed to so much political influence, and state-level spread impacts the country's COVID-19 spread, which worsened throughout the rest of the year 2020.

Table 5.2: Intra-State Significant Test Results and Facebook Interaction Data

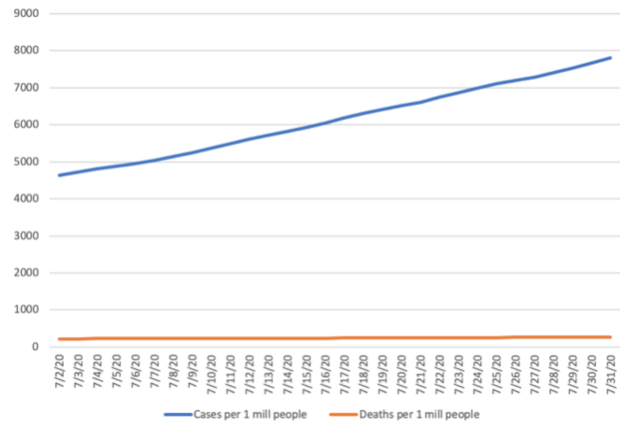
State	Policies	Sample Size	Sample Mean	Alternative Hypothesis	p-value	Reddit or Twitter Dataset Used in Significance Test	Facebook % Positive Interactions (like, love, care)	Facebook % Negative Interactions (sad, angry)
Arizona	Shelter	906	-0.029641	μ shelter < μ school	9.10E-24	Reddit weighted	54.27	41.59
	School	349	0.375731				67.36	27.78
Arizona	Masks	502	0.146942	μ masks > μ school	1.65E-05	Twitter combined weighted	N/A	N/A
	School	33	-0.000336				67.36	27.78
California	Masks	6939	0.072713	μ masks < μ school	0.00E+00	Twitter combined weighted	92.93	1.59
	School	5090	0.315874				97.31	2.00
Florida	Masks	683	0.067201	μ masks < μ shelter	2.18E-02	Reddit weighted	N/A	N/A
	Shelter	4353	0.123542				N/A	N/A
Iowa	Shelter	6085	-0.047046	μ shelter < μ school	7.89E-06	Reddit weighted	72.58	25.19
	School	34	0.439100				66.86	29.98
Michigan	Masks	3674	-0.095808	μ masks < μ school	2.43E-60	Twitter combined weighted	95.22	3.29
	School	3765	-0.041069				97.74	0.83
Nevada	Masks	944	0.014831	μ masks < μ shelter	1.73E-17	Reddit weighted	83.12	14.67
	Shelter	1098	0.259457				96.86	2.18
New York	Shelter	12877	0.148421	μ shelter < μ school	2.26E-10	Reddit weighted	97.59	0.74
	School	1734	0.246463				79.32	16.31
New York	Masks	49	0.009951	μ masks > μ school	1.57E-02	Twitter combined weighted	97.92	1.09
	School	1911	-0.053007				79.32	16.31
Ohio	Masks	5364	0.229566	μ masks < μ shelter	3.89E-05	Reddit weighted	79.23	17.55
	Shelter	5982	0.276778				96.05	2.73
Ohio*	Masks	5364	0.229566	μ masks > μ school	1.11E-20	Reddit weighted	79.23	17.55
	School	194	-0.233408				92.73	5.54
Ohio	Shelter	5982	0.276778	μ shelter > μ school	3.71E-32	Reddit weighted	96.05	2.73
	School	194	-0.233408				92.73	5.54
Ohio*	Masks	1201	0.057365	μ masks > μ school	2.09E-50	Twitter combined weighted	79.23	17.55
	School	411	-0.123398				92.73	5.54
Pennsylvania	Masks	1108	0.346921	μ masks > μ shelter	1.72E-03	Reddit weighted	74.04	7.12
	Shelter	361	0.234973				94.93	2.85
Washington	Masks	53	0.018086	μ masks < μ school	7.50E-12	Twitter combined weighted	84.33	12.58
	School	342	0.242448				79.99	14.94

Table 5.3: Demographics and Political Party Affiliations by State

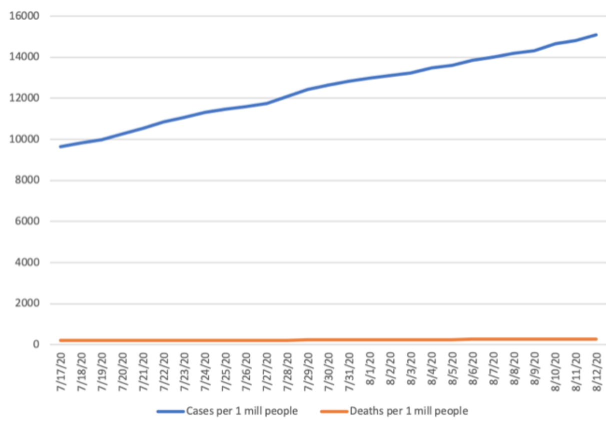
			% of adults who identify as... (14)		
State	Population in 2019 (16)	Governor Party Affiliation in 2020 (32)	Republican/lean Rep.	No lean	Democrat/lean Dem.
Arizona	7,278,717	Republican	40	21	39
California	39,512,223	Democrat	30	21	49
Florida	21,477,737	Republican	37	19	44
Iowa	3,155,070	Republican	41	19	40
Michigan	9,986,857	Democrat	34	19	47
Nevada	3,080,156	Democrat	37	18	46
New York	19,453,561	Democrat	28	19	53
Ohio	11,689,100	Republican	42	18	40
Pennsylvania	12,801,989	Democrat	39	15	46
Texas	28,995,881	Republican	39	21	40
Washington	7,614,893	Democrat	33	23	44
Wisconsin	5,822,434	Democrat	42	16	42



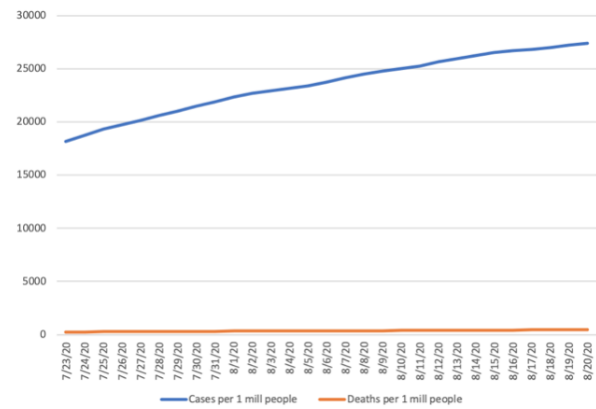
a) Arizona COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy



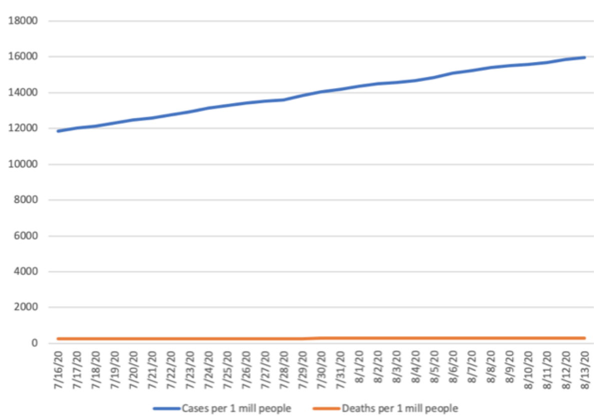
b) Ohio COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy



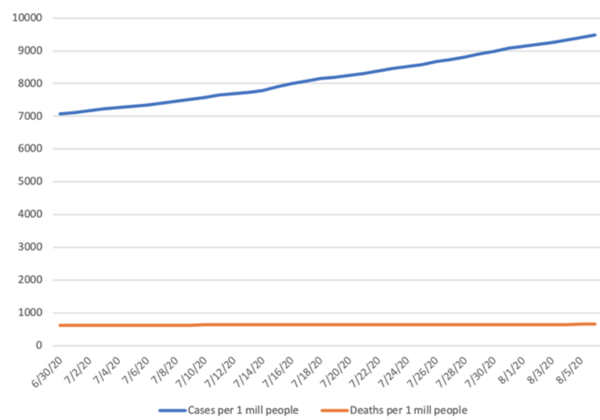
c) California COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy



d) Florida COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy

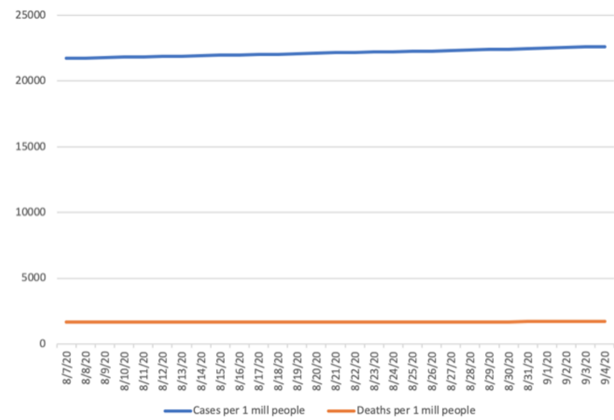


e) Iowa COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy

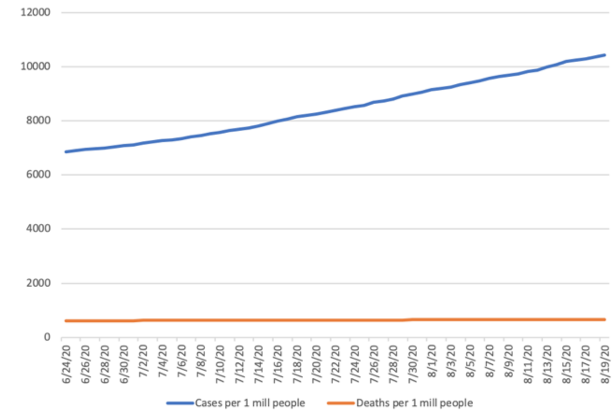


f) Michigan COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy

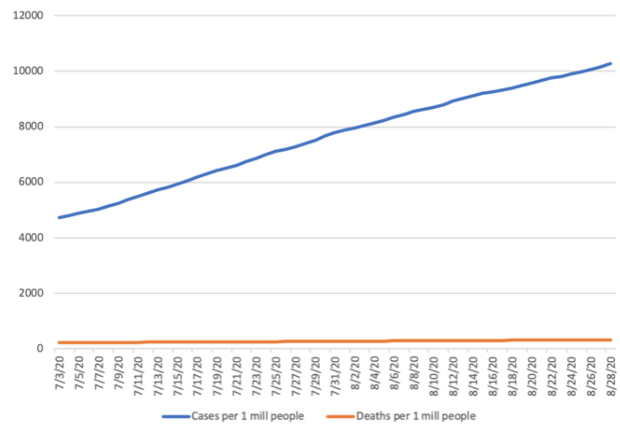
Figure 5.1: COVID-19 Cases and Deaths After Announcement of State-Specific Policies (a-f)



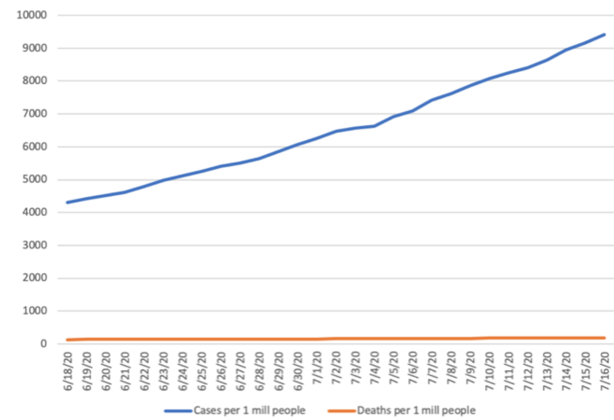
g) New York COVID-19 Cases and Deaths after Announcement of Fall School Reopening Policy



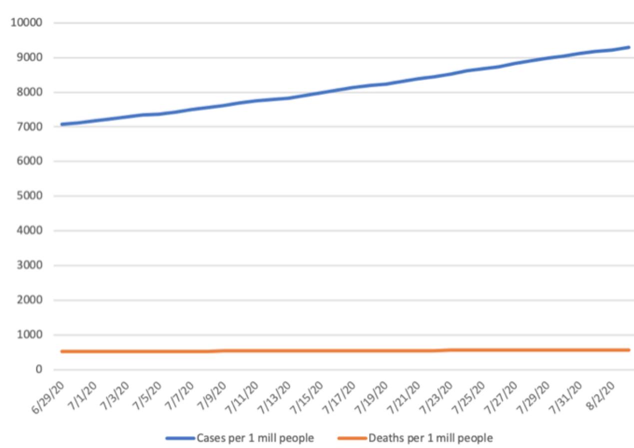
h) Michigan COVID-19 Cases and Deaths after Announcement of Mask Policy



i) Ohio COVID-19 Cases and Deaths after Announcement of Mask Policy



j) California COVID-19 Cases and Deaths after Announcement of Mask Policy



k) Pennsylvania COVID-19 Cases and Deaths after Announcement of Mask Policy

Figure 5.2: COVID-19 Cases and Deaths After Announcement of State-Specific Policies (g-k)

Chapter 6

Development Timeline

See Figures 6.1, 6.2, 6.3, and 6.4 for the legend and development timelines for the fall, winter, and spring quarters.

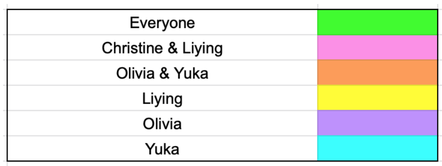


Figure 6.1: Development Timeline Legend

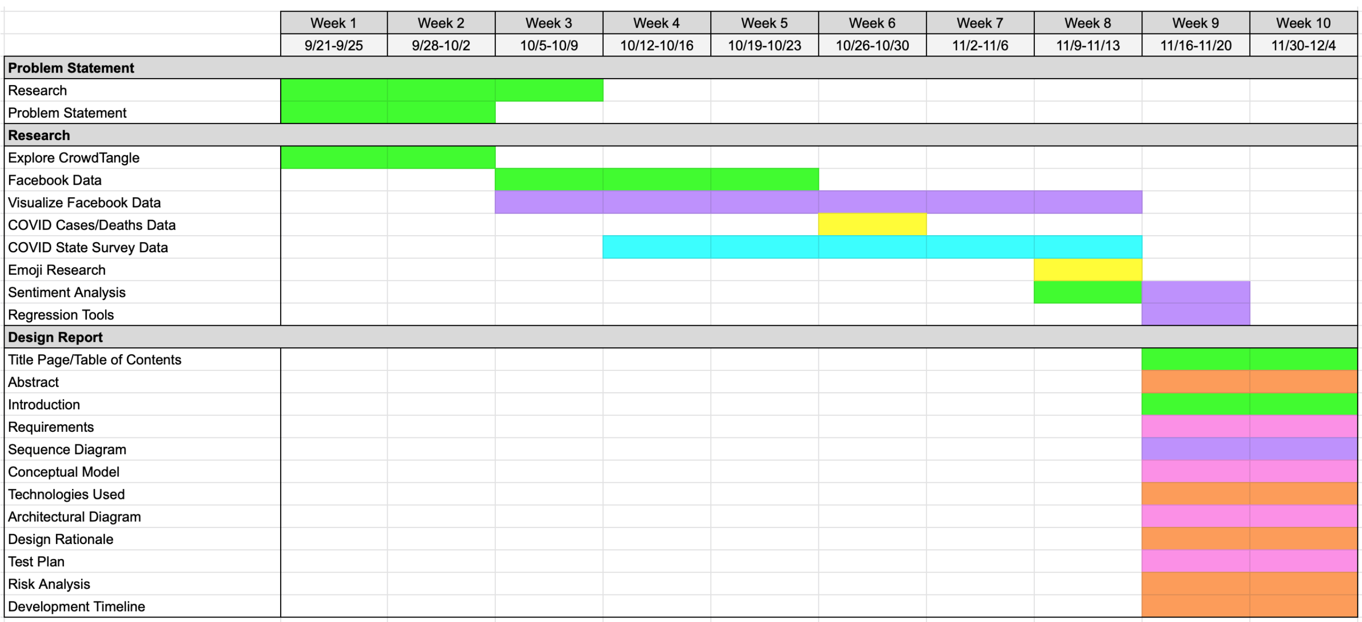


Figure 6.2: Fall 2020 Development Timeline

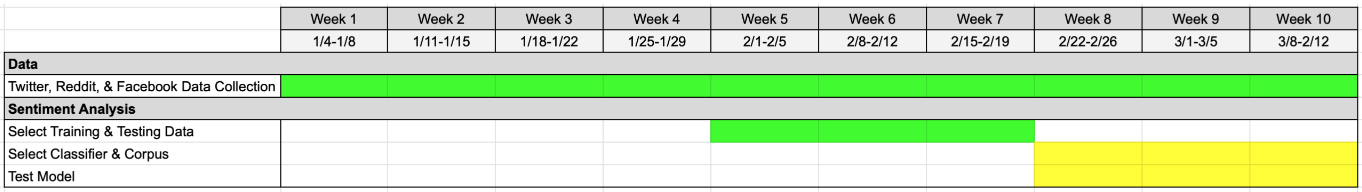


Figure 6.3: Winter 2021 Development Timeline

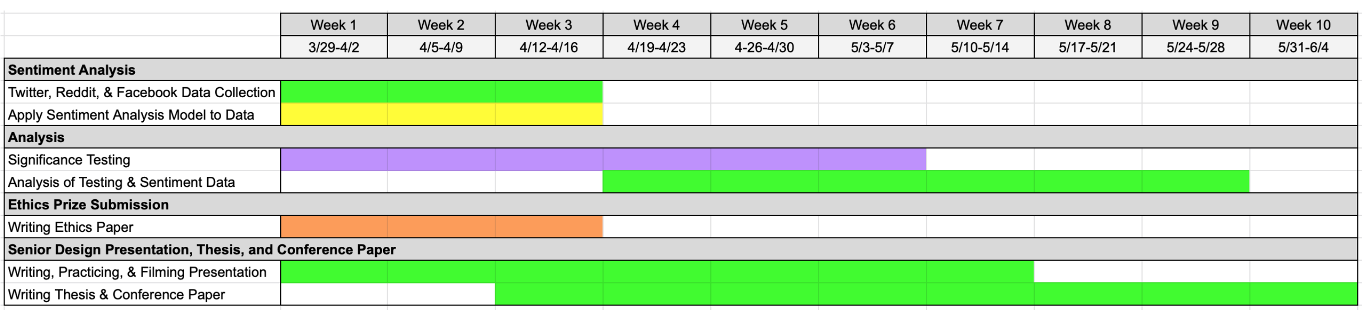


Figure 6.4: Spring 2021 Development Timeline

Chapter 7

Project Risks

See Table 7.1 for the risks involved in our project. We list the risk itself, the consequences that would follow, the probability of that risk occurring on a scale from 0 to 1, the severity of how serious the risk is on a scale from 0 to 10, the impact of how much influence that issue would have on the entire project, and the mitigation techniques to help prevent those risks or what to do should they occur.

The more severe risks involve not completing our goals within the time we have for this project. We prevented these risks by working along our development timeline and planning for slack time to be able to deal with any issues as they occur. One of the most severe risks is loss of source code, such as the natural language processing, data collection, or significance testing code. We avoided all the risks summarized in Table 7.1 by using GitHub and Google Colaboratory for version control, Trello for project management, and meetings on a weekly basis for communicating within the team and our faculty advisor.

Table 7.1: Risk Analysis for Research and System

Risk	Consequence	Probability	Severity	Impact	Mitigation
Time to complete research	Insufficient/weak analysis	0.2	9	9	Create realistic schedule with slack time and stick to it.
Time period for COVID data collection	Insufficient/weak analysis	0.3	5	5	Collecting data across a realistic, manageable, and eventful time period. Comparing the selected time period against other time periods to ensure it yields robust results.
Loss of source code	Source code for website is lost and we have to redo it	0.3	10	9	Use GitHub and Google Colaboratory version control properly and consistently.
Bugs	Code does not work as intended	0.8	7	3	Test often and thoroughly. Include time in schedule to account for bugs and debugging.
Unathorized overwriting on source code	Source code is lost and we have to redo it	0.3	7	4	Use GitHub and Google Colaboratory version control properly and consistently, and stay organized amongst tasks.

Chapter 8

Societal Issues

8.1 Introduction

Our research is data driven, which is precisely why ethics plays a vital role in the efficacy of our project. The computing sector of the tech industry has largely been characterized by the famous Facebook motto coined by Mark Zuckerberg, “Move fast and break things” (78). This sentiment has pushed the tech sector towards seemingly impossible advancements, but in the wake of endless achievement, ethics is often an afterthought. With the tech sector supporting 18 million US jobs and representing 12 percent of the US gross domestic product (GDP) (61), it is clear that technology is a significant part of society. Hardware and the programs that run on it are integrated with virtually every aspect of our lives, from the computers and smartphones we use for communication, to the cars and planes that transport us, down to the coffee machines that make our morning espresso. Given the ubiquitous nature of technology in our daily lives, ethics in technology and how it impacts end users should be the foremost priority. At Santa Clara University (SCU), young computer scientists are taught that ethical consideration should be incorporated into every step of a project so that when they are working in industry, it will be ingrained into the foundation of every product they build. Likewise, while our project’s findings pave the way for pressing questions and novel discussions, they also help our team understand the ethical implications of the tools that we use. Inspired by the ACM Code of Ethics (15), we analyze our methodologies of data collection and what that means for the computing field as a whole.

8.2 Ethical Justification

Section 1.3 of the ACM Code of Ethics states, “Be honest and trustworthy” (15). This rule led us to closely examine the tools we use for this work: APIs. APIs are services offered by social media conglomerates, such as Facebook, Twitter, and Reddit, that allow developers to create social media bots and collect public user data at a large scale. In recent years, there has been an increase in technology like bots being used to disseminate misinformation, influence public opinion, and manipulate online discourse, often based on some malicious agenda. Futuristic automated technology is not the only exploitative threat to online users—humans are, too. Internet shills are users hired by an organization or entity to promote an idea or agenda by specifically combating any opposing opinions (60). Thus, their end goal is very similar to those of bots, they just perform with a different methodology. While bots are often used to strengthen and agitate those who already believe in a certain idea, internet shills blend in with their peers in order to sway their opinions and make them believe that the general consensus of users is the opposing idea. Group polarization is a social construct that shows how putting like-minded people in a group reinforces each other's viewpoints and causes their opinions to strengthen. Researchers found that groups who hold a tentative consensus become more extreme in their opinions after discussing topics as a group. The researchers concluded that "group consensus seems to induce a change of attitudes in which subjects are likely to adopt more extreme positions" (64). When people are uncertain about their opinions but see that others agree with them, their conviction towards that opinion, whether it is positive or negative, becomes stronger (64).

Not only is the practice of making manipulative bots becoming increasingly commonplace, these bots are often created in large batches that work together to amplify their agenda (57). Designing bots that create a false sense of general agreement and influence the public's opinion with malicious intent is dishonest and untrustworthy. It is wrong to manipulate people and can be downright harmful in some situations, such as during the 2016 US Presidential election. In a study from 2016, researchers found that in over 20 million tweets collected using election-related hashtags during and around the election, over 3 million of those were bot-generated, and these bots were algorithmically designed to "alter public opinion and endanger the integrity of the Presidential election" (43). A similar danger of social media bots is the potential for misinformation dissemination, which has also been widely studied and shown to be driven by a combination of bots and fake news (87). Studies have shown that Russian social networks interfered heavily in Italy's social discourse regarding immigration and xenophobia on Twitter in 2017, and they spread messaging through Facebook in several African countries in 2019 to better their reputation (40; 62). It is clear that harmful bots and internet shills pose large threats to social network users, platform integrity, and the targets of these malicious actors, and APIs make it much easier for mal-intentioned users to create such entities.

While we primarily use the ACM Code of Ethics (15) to guide our computing practices, we reviewed several ethical frameworks discussed in Chapter 6 of the SCU Engineering Handbook (10) and the Markkula Center for Applied Ethics' "A Framework for Ethical Decision Making" (2) in order to have the most holistic and well-rounded approach to conducting our research. We have seen throughout the pandemic that people's actions can have grave consequences when it comes to COVID-19, and policies are there to protect people and the overall common good, though they only work if people abide by them. The deontological approach to ethics highlights the importance of following established rules in order to decide between what is right and wrong. This approach does not suffice when the rules have not yet been created, which has been observed in the US with states passing different rules for how to handle the spread of COVID-19, causing people to believe opposing actions are right. Meanwhile, the utilitarian approach promotes ethical actions that produce more good than harm and the common good approach relies on common conditions that must be met for all in society, specifically the most vulnerable, in order to ensure everyone's needs are met. On the social media side, there are no universal rules for how social media companies should be protecting data and users from things like misinformation and fake news, so people and companies cannot rely on simply following the rules. The most informative approach for our project is to apply aspects of virtue ethics alongside deontology, utilitarianism, and the common good approach, because individually they are not enough to inform our process. We cannot abandon reason and caution for the sake of advancement, while we also cannot regulate ourselves so harshly that no progress can be made. Ultimately, the best practices are those that allow for cultivated innovation that gives thoughtful consideration to the impact that it will have on the world and the people in it.

With all of these ethical concepts in mind, we as engineers strive to solve issues and consider the needs of all people, challenging ourselves with the notion of, "What kind of person will I become if I do this?" (2). Society needs to better understand how people react to COVID-19 policies and how their reactions compare to COVID-19 cases and deaths so that our governance can work with the community to better protect people, especially the vulnerable. In addition, our research raises awareness of the dangers of social media, which hopefully will alert users about safe social media usage and encourage academia and society to demand greater regulation of the tech industry. We aim to add to the conversation about the tech sector's lacking consideration towards ethics and accountability because these issues may lead to life and death situations, such as if people are exposed to misinformation on social media regarding COVID-19. We use these ethical frameworks (10; 2) and the ACM Code of Ethics (15) as guides for this project to inform decisions that will produce a body of work that will both benefit society and contribute to our field. We apply our ethical decision-making skills throughout every step of our project, especially in our usage of these social media APIs for our research.

8.3 The Character of an Engineer

For our project, we had to sign up for the APIs of Facebook, Twitter, and Reddit in order to access public user data. Each team member was required to make a Facebook account in order to access Facebook's API, CrowdTangle (1). According to CrowdTangle's website, the service is available for academic researchers and "media publishers, sports leagues, music labels, public figures, and content creators", and users must submit an application to gain access (1). For Twitter's API (12), each team member applied for an API account, which involved creating a Twitter account and describing our project in detail. We were granted access to the API after answering further questions about how we would be using the data gathered through their service and whether we would be publishing any user data we gathered. Finally, to access Reddit's API (8), all we had to do was create a Reddit account, and then we were granted immediate access to its capabilities.

In all of these cases, we had to sign the Terms of Service of the API, an agreement which involved rules such as restrictions on publishing the data collected and limitations on how much data we are able to collect (11; 13; 9). These terms are algorithmically enforced through the API services, such as through data caps, however, the platforms only have so much power. If a developer wants to create a social media bot to disseminate misinformation or secretly collect and sell user data, it is virtually impossible to catch all instances of misconduct on social media. Social media companies have worked to develop machine learning algorithms to detect such malicious social bots and remove them from their platforms, but this approach is not fool-proof since malicious bots may be extremely sophisticated, causing the algorithm to fail (48). Even if the algorithm is able to find malicious bots and remove them, often the damage the bots have done is irreversible with respect to influencing public opinion, disseminating misinformation, and collecting data. Additionally, it is extremely difficult to identify the creators behind these social media bots, so the odds of holding them accountable or discouraging them from doing it again are slim. Another danger of social media bots relative to academic research and this project is that we cannot be sure that the data we collect is created by humans and not by bots or shills. This means that academic research and social media data collection are subject to data generated by these entities that may sway the conclusions and decisions made by researchers and developers. Unfortunately, it is becoming a reality that research could be built upon false data on social media.

While our team members and many other researchers and developers follow the rules and limitations of these APIs, thereby valuing Section 2.3 of the ACM Code of Ethics, “Know and respect existing rules pertaining to professional work”, others take advantage of these services’ flexibility and lack of regulation for their own malicious purposes [4]. Additionally, social media companies are solely responsible for developing the Terms of Service without any extensive policies guiding their rules. The European Union’s General Data Protection Regulation (GDPR) (3) and the California Consumer Privacy Act (CCPA) (30) provide some regulation in their respective jurisdictions, but these are geographically bounded and by no means provide any universal guidelines for tech companies. Even if such policies are passed at the federal level in the United States and in more countries, companies will have to redesign their platforms to ensure compliance with new policies, and enforcing such policies on every platform is virtually impossible without greater oversight by enforcement agencies due to the sheer volume of internet usage and applications. Until that happens, society entrusts the companies to set the standards for user privacy and to protect the consumers, which fails in practice as shown in data breaches that leave millions of users exposed to attackers and misinformation schemes on countless social networking sites that have impacted elections and public discourse (43; 87; 65).

On the user side, those who sign up for accounts on social media platforms are unlikely to read the Terms of Service nor Privacy Policy, which are often extremely technical and laced with legal jargon that confuse the average user. A study from 2017 found that 97 and 93 percent of users accept the Terms of Service and Privacy Policy respectively without reading the contents fully, with most quickly skimming over the content (85). This issue adds a layer of complexity to the ethical considerations of these services, since most users are not fully aware of what they are agreeing to when they sign up for an account. Had they been made fully aware of the platform’s policies, the users might have chosen not to make an account at all. This duplicity further escalates the need for strong legislation and regulation of the tech sector so that consumers are protected and can agree to platform policies in good faith.

8.4 Ethical Pitfalls

For our project, we employed rigorous rules and overview in order to ensure responsibility and data integrity. Each social media platform has its own unique challenges that pose a risk to user anonymity as well as validity of the data itself. Reddit is a social media site where users tend to avoid posting personal information of any sort, whether it be a profile picture or their real names. In order to respect user privacy and anonymity, we are only studying the aggregated results of statistical analyses and tests on the data collected from user comments. Furthermore, while Reddit is rife with bots, user-made bots often disclose their status with a simple “I am a bot” in the message of their posts and can cite their creator as well. Subreddits, which are individual communities built around specific topics in which the members are interested, such as r/news and r/COVID19, are moderated by members of the community. The moderators are tasked with removing spam, comments, or even users that do not follow the community guidelines. These subreddits make up the entirety of Reddit and effectively police themselves.

For our Twitter data collection, we collect replies to manually reviewed tweets from governors about COVID-19 policies throughout the pandemic. Since Twitter's API only allows users to fetch data from the past 7 days, we have to rely on data collected in other studies. In order to retrieve Twitter data from the year 2020, we are using a dataset available on IEEE DataPort with tweet IDs collected since March 15, 2020 to the present that contain common COVID-19 keywords and hashtags (70). The dataset only contains tweet IDs and not tweet content, so other authorized users of the API can use the tweet IDs to retrieve the full tweet data. This dataset limits our research since we only have access to historical tweets that were collected using this researcher's COVID-19 keywords. Additionally, Twitter has similar challenges to Reddit in that the data is constrained by the context of the platform. The demographic of people that use Twitter, the type of content they post, and the amount of community discourse on the platform all can contribute to the sentiment of their tweets. While these variables are out of our control as researchers, they are nevertheless controlling factors of the data, and therefore important to note. In addition, we may have collected content that was posted by bots on Twitter, which may skew our results, but we have no way to differentiate bot-generated content from human-generated content. We can only rely on Twitter's internal bot-detection algorithms to remove such content. Just as with Reddit, we are only studying results of statistical analyses and tests on this data rather than on the specific user data or post contents. If we choose to share this dataset with the academic research community, we will only be posting the tweet IDs, in accordance with the Twitter API policies (13). Our Facebook dataset only contains the number of likes, shares, and comments to specific posts from governors about COVID-19 policies and guidelines rather than user comments like we have from Reddit and Twitter. Nevertheless, we are only studying the overall sentiment and aggregated results of this data to protect user privacy and anonymity.

With any data science research, it is nearly impossible to remove all noise from the dataset, but we have done meticulous research to learn the best data collection and data science methodologies as well as understanding the underlying technology of the social media platforms in order to do our due diligence. Data integrity is the key to robust research, so we have written quality code that in turn generates quality data, removed as much of our own biases as we could, and focused on the quantitative facts that are produced from our data to certify the significance and validity of our research results. We worked to ensure our data collection code functions as expected and follows procedures we studied in related works, and we tested our code vigorously. We also relied on popular techniques for sentiment analysis and machine learning, which, while not perfect, are considered the state of the art in our field. All assumptions made in our research were heavily discussed as a team and with our advisor to ensure that we could validate them using related research, which also provided context for our decisions and helpful knowledge about how to perform this research. The knowledge gained from prior work is the primary support for our research, and our goal is similarly to contribute to our field and support future work in this novel topic regarding the COVID-19 pandemic.

While the results of our work may lead to more scientific advances that benefit society, such research can be construed in many ways if it is not presented clearly alongside the limitations and challenges that exist in our data collection and the context of our work. As a team we have learned about the importance of Section 2.2 of the ACM Code of Ethics, "Maintain high standards of professional competence, conduct, and ethical practice" (15). In comparison to academic research, in industry, whatever an engineer produces is typically for generating profit. The saying, "If you're not paying for the product, you are the product", describes the reality of monetized services and products in the tech industry, of which many users may be unaware. For example, social networking platforms may be free to use, but the users actually become the product from which the social media companies profit by way of advertising revenue. The lack of regulation for such services and products leads companies to have more freedom to maximize their profits in different ways, possibly at the expense of the user's security and privacy. There is not as much of an expectation of transparency and honesty in the tech industry as there is in research because the latter is performed for the betterment of society and has already been subject to extensive ethical review. In order to contribute to the human wealth of knowledge, society must trust the work of academic researchers, who in turn must abide by strict ethical standards in all fields. We strive to maintain the trust that people put in academic research and the computing discipline by upholding standards and being transparent in every aspect of our process.

Another key principle of the ACM Code of Ethics that we have taken seriously is Section 2.7, "Foster public awareness and understanding of computing, related technologies, and their consequences" (15). Through this work, not only have we learned more about the ways in which data can be compromised and abused by malicious actors, but also its potential for advancing the pursuit of knowledge. Our research analyses and results help us to better understand the state of public sentiment surrounding COVID-19 policies and guidelines in addition to the dynamics of public health messaging on social media, which is a novel usage of such platforms. Our work also raises awareness of social media bots and shills that may skew social media research, the dangers of malicious bots, and the ease with which users can sign up for social media APIs and the subsequent abuse of these services. By completing our senior design thesis, we will contribute to society's understanding of the COVID-19 pandemic and the ways people responded to policies and guidelines over time in the US, as well as raise awareness to the potential threats that bots and shilling pose to both the public and academic research.

8.5 Conclusion

Given all the ethical issues and research challenges our senior design project has uncovered, we as a team have deliberated at length about the assumptions, methodologies, and analysis approaches in our project in order to uphold the ACM Code of Ethics (15), our personal codes of ethics, and the institution of academic research. In the tech industry, users entrust companies to build secure systems because they believe that the engineers are following their profession's code of ethics. While students at Santa Clara University are challenged to consider ethics in all aspects of their curriculum, not all those who become engineers and work at these companies are subject to the same education. Computer scientists belong to a field that does not require them to obtain a license to work as an engineer nor mandates compliance with a specific ethical code, as is true for other fields, such as civil engineering. Being a good engineer means following one's professional code, as well as acting ethically even when no one is watching. It is vital to innovate while heavily weighing the implications of all design decisions and move slowly if it means protecting the users of such systems. Consumer privacy, data protection, and potential for harm should be just as vital to the project as resources, timelines, and stakeholders. These changes require monumental shifts in the way that computer scientists are taught to create. Until there are sweeping regulations on technology and consumer privacy, as well as teachings that emphasize building comprehensive systems, the engineers are in charge of regulating themselves. There is no ruleset that is absolute and will provide the correct answer to every situation, as deontology would lead us to believe. Instead, each action should be informed by a careful and nuanced analysis that applies several ethical frameworks, like we have done with our work. At the end of the day we must strive to live virtuously and hold ourselves and each other accountable for our actions in order to create a more ethical and technologically sustainable world.

Chapter 9

Conclusion

9.1 Concluding Remarks

Our goal was to answer the following questions:

RQ1. How does public sentiment in response to COVID-19 policies compare between different states and policies?

RQ2. Does public sentiment parallel the spread of COVID-19?

RQ3. Is social media a good indicator of people's feelings towards policies?

We answered the above research questions by collecting social media data from Facebook, Reddit, and Twitter and performing sentiment analysis and significance testing to compare average sentiments between and within states for three COVID-19 public health policies; shelter-in-place orders, mask and face covering guidelines, and fall school reopening policies. We conducted significance testing on the average sentiments across all states for each policy and found that the average sentiment in response to mask policies is statistically significantly greater (p-value<0.05) than that of shelter-in-place policies and fall school reopening policies across all states studied. This may indicate that people were more positive about mask policies in general when compared to shelter-in-place and fall school reopening policies, which partially addresses RQ1.

To further address RQ1, we conducted inter-state and intra-state significance tests on the average sentiments of social media content regarding state policies implemented by governors. From our inter-state significance testing, we found that there are significant differences in sentiment between several states for fall school reopening and mask policies. Among the inter-state tests on fall school reopening policies, we found that replies to and comments about policies from the governors of Arizona, California, Florida, Iowa, Michigan, and New York had statistically significantly higher average sentiments (p-value<0.05) than did those of Ohio, which parallels reporting related to how people in Ohio responded to the pandemic in 2020. Among the inter-state tests on mask policies, we found that replies to and comments about policies from the governors of California, Ohio, and Pennsylvania had statistically significantly higher average sentiments (p-value<0.05) than did those of Michigan, which also parallels reporting about Michigan's pandemic response and contention. The results for the inter-state tests also address RQ3 since it seems that our results parallel the reporting in Michigan and Ohio about people's responses to their respective governor's policies.

Additionally, many states for which we found statistically significant higher average sentiments (p-value<0.05) than other states had higher COVID-19 case counts and/or case increase rates, which may indicate that as COVID-19 spread worsened, people were more positive about policies implemented in those states, addressing RQ2. We found that the majority of states that had statistically significant differences (p-value<0.05) in average sentiment in response to different state policies were swing states in 2020 (90; 26), which may indicate that the politicization of COVID-19 topics, shown by previous works (86; 37), plays a role in how people respond to state policies, addressing RQ3.

We conclude that while there are statistically significant differences between public responses to state-level policies, future work must more closely explore the factors that explain these differences, such as political party distribution and platform demographics. Examining what factors contribute to sentiment differences may help government and public health officials communicate with the public more effectively, which can help society as a whole respond better to public health situations in the future.

9.2 Future Work

This study has provided many ideas for future work to further investigate the public's reaction to public health policies and whether there are factors that can explain the differences in sentiment for different groups of people. This study could be expanded to include all 50 states in the US to provide a more comprehensive view of the public sentiment towards COVID-19, and include more policies that were implemented throughout the pandemic. We suggest future work be done to explore the specific factors that contribute to differences in public sentiment, such as demographics, political party affiliations and distributions, platform user base differences, and policy-specific details.

There are aspects of this study that could be improved upon in future work. We could refine our sentiment analysis by making a more sophisticated model for the relationship between nested comments on Reddit and nested replies on Twitter, which could yield more accurate sentiment scores based on peer interactions. Additionally, we could collect Twitter data ourselves rather than using a preexisting dataset, which was collected with a certain set of keywords that were out of our control. If we were able to collect Twitter data with our own parameters, we could have a more complete dataset that reflects more replies and interaction with the governors' posts.

Finally, this study approach can be applied to more countries and topics, such as vaccine hesitancy or non-COVID-19 topics, such as gun and reproductive health laws, to determine how people respond to laws in their state and the country as a whole. This work could also be performed on other social media platforms, such as YouTube and Instagram, which would give an even more diverse view of public sentiment on social media.

9.3 Acknowledgements

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