Analyzing the Relation Between Government Anti-Contagion Policy Severity and United States COVID-19 Epidemiological Data

Jenny Wei

Abstract

Since the first emergence of the SARS-CoV-2 virus in Wuhan, China in December of 2019, the virus has spread to 216 countries and territories, infecting over 16.3 million people globally. To combat the COVID-19 pandemic, governments are implementing unprecedented anti-contagion policies with little known effects. Measuring the impact of anti-contagion policies would help governments make informed decisions and design effective policies for stopping the spread of COVID-19. In this work, we introduce an approach to assess United States policy severity by analyzing U.S. state government Twitter tweets using a random forest ensemble model. While previous studies have measured country-level effects of anti-contagion policies, we measure the relation between policy severity on U.S. state-level COVID-19 epidemiological data. We show that our method is able to quantitatively evaluate state government tweet severity and analyze both tweet severity and COVID-19 prevalence, hospitalization rate, and death rate for U.S. states. Future directions involve predicting COVID-19 trends from policy severity to quantify the effects of anti-contagion policies of various strengths.

1 Introduction

Since the first emergence of the SARS-CoV-2 virus in Wuhan, China in December of 2019, the virus has spread to 216 countries and territories around the world, infecting over 16.3 million people [1]. In the United States, the first case of COVID-19 was reported in the state of Washington in January of 2020, and according to the Centers for Disease Control and Prevention, the United States now accounts for over 25% of global COVID-19 cases: over 4.2 million people have been diagnosed with COVID-19 in all 50 states [2]. In the wake of this pandemic, governments are implementing policies designed to limit the spread of the coronavirus. These policies aim to restrict person-to-person contact and consist of, but are not limited to, banning group gatherings, restricting travel, closing schools and businesses, and encouraging social distancing and mask wearing. However, the impacts that these policies have on reducing the spread of COVID-19 are often unknown due to the unprecedented nature of the COVID-19 pandemic [3].

A major challenge to implementing policies lies in the economic costs that come with stay-at-home orders: reduced business activity leads to job losses, drops in economic activity, and increased government debt levels [4]. Many states in the U.S. are hesitant to put in place anti-contagion policies that have the potential to be detrimental to the economy, but do not have clear effects on reducing COVID-19 spread, all the while COVID-19 infection rates steadily rise across the U.S. Analysis of the effects that these anti-contagion policies have on COVID-19 infection rates could provide state governments with knowledge on what policies to implement in order to limit the spread of the coronavirus [5].

Several works address the impact of anti-contagion policies in multiple countries using open-source epidemiological data and policy data [3, 5, 6, 7]. These studies use epidemiological compartmental models (e.g. SIR model) to predict how various categories of anti-contagion policies affect the number of cases in specific locations. However, these works are conducted only on a country-wide scope and do not specifically address the varying severities of policies. Futhermore, these studies are impractical to conduct on a U.S. state-wide scale due to the difficulty of cataloging constantly changing policies that differ between many states.

In this study, we analyze the impact of specific policy severity on COVID-19 cases in the United States. In order to study this, we obtain Twitter tweets regarding anti-contagion guidelines and policies from U.S.

state government Twitter handles. We develop an approach to analyzing guideline severity and the impact of guideline severity on COVID-19 epidemiological data using natural language processing techniques and statistical analysis tools. We show that our method is able to effectively classify tweet severity and analyze the relation between tweet severity and COVID-19 prevalence, hospitalization rate, and death rate for individual U.S. states.

Finally, because our method is able to analyze anti-contagion policy severity, as well as the correlation between policy strength and COVID-19 data, it enables future work to be done on predicting how different levels of policy severity affect various measures of the COVID-19 pandemic, including, but not limited to, case count, hospitalization rate, and death rate. Our hope is that by modeling the relation between anti-contagion policy strength and COVID-19 epidemiological data, governments will be able to make informed decisions on policy implementation to better limit the spread of the COVID-19 disease.

2 Literature Review

2.1 Text Feature Selection Via Topic Modeling

In recent years, topic modeling has emerged as a standard tool for text feature selection, the selection of relevant features for document analysis [8]. A common form of topic modeling is Latent Dirichlet Allocation, an unsupervised probabilistic topic model for analyzing corpora, first proposed by Blei et al [9]. Latent Dirichlet Allocation assumes that for a given corpus containing M documents, the documents represent a distribution of T topics, and each topic is composed of a word distribution θ. For each document in the corpus, a topic z is sampled from the word distribution θ of the document, and a word w in θ that is associated with z is also sampled. This process is repeated N times, N being the number of words in the document, for each document in M. Every document is therefore represented as a probability distribution of T topics, with the distributions for each document varying depending on the word distribution θ of the document [10]. Latent Dirichlet Allocation models have consistent performance on short texts, including tweets, and by representing tweets as a distribution of topics, tweets can be aggregated into groups based on their dominant topic. This is particularly useful for gathering documents from Twitter: during the process of tweet mining, many irrelevant tweets are introduced into the dataset, and Latent Dirichlet Allocation can be used to prune irrelevant tweets, thereby extracting only the relevant features of a text corpora [11].

2.2 Supervised Approaches to Text Classification

Many approaches to text classification exist, the most common algorithms being decision trees, Naive-Bayes, K-nearest neighbors, logistic regression, and support vector machines. Naive-Bayes, K-nearest neighbors, and logistic regression are often used due to their simplicity, but their performance is suboptimal when analyzing text corpora containing larger amounts of documents [12]. Support vector machines are the most popular method for text classification due to their high precision, but tend to have poor recall scores. Decision trees are often combined together into random decision forests, an ensemble classification approach. Random forests are able to achieve high accuracy for text classification, but face the risk of overfitting [13].

2.3 Feature Extraction

A fundamental component of text classification lies in feature extraction, the conversion of unstructured documents to structured feature spaces. In order for a text corpora to be processed by text classification algorithms, the documents must be converted into n-dimensional data [14]. One method of feature extraction is Word2vec, a group of language models proposed by Mikolov et al. that create word embeddings [15]. Unlike rules-based embedding methods such as TF-IDF, which creates a matrix representation of a document by counting the term frequency of individual words, Word2vec models implement a state of the art two layer neural network approach to generate word embeddings, vectors that capture the semantic meaning of a document. One architecture of Word2vec is the Continuous Bag-of-Words model (Fig. 1). For each word in a document, the model one-hot encodes the future and history words surrounding the target word and inputs the encodings into a neural network, with the goal of correctly predicting the target word. The vector embedding of the target word is then generated by taking the dot product of the neural network's weight and the one-hot encoding of the target word [16].

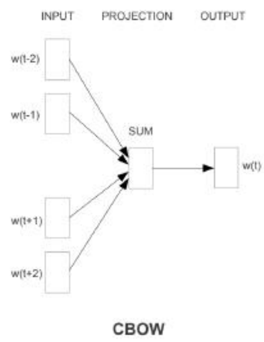

Fig. 1: Word2vec Continuous Bag-of-Words architecture. The CBOW model uses the surrounding words to predict the target word [16].

2.4 COVID-19 Tracking Via Twitter Data

Several studies have been published regarding the analysis of COVID-19 related Twitter data. Most notably, Singh et al. collected geotagged tweets containing phrases related to COVID-19 and evaluated the relation between tweet volume, tweet themes, and common phrases used in tweets with COVID-19 case counts in several countries. Furthermore, the study investigated the quality of information and level of misinformation in tweets, drawing the conclusion that Twitter conversations are a viable source for predicting the spread and outbreak of COVID-19.

Current studies involving the analysis of Twitter data exhibit the applicability of using Twitter data to model and predict the COVID-19 pandemic. However, these studies only compile general user tweets related to COVID-19, and to our knowledge, no publications regarding government COVID-19 tweet analysis have been released.

2.5 Anti-Contagion Policy Effect Analysis

Previously, studies have been conducted to investigate the impact of government interventions on the COVID-19 pandemic. Hsiang et al. [3] evaluated the effects of large-scale anti-contagion policies on the COVID-19 epidemiological data in China, France, Iran, Italy, South Korea, and the United States. A total of 1,717 policies were collected from January to April of 2020, and COVID-19 data regarding cumulative cases, recoveries, and deaths was acquired from each of the six countries. Compartmental SIR models, a type of epidemiological model which divides a population into three compartments (susceptible, infectious, and recovered) and applies differentiation to model the spread of a disease, were used to predict the effect of policy implementation on COVID-19 cumulative case numbers. The study found that implementation of combined policies lead to statistically significant reductions on the number of COVID-19 cases and COVID-19 infection rate (Fig. 2).

Another study by Dergiades et al. [7] measured the effect of government policy strength on COVID-19 mortality rates. Dergiades et al. compiled policy stringency indices for 32 countries from the University of Oxford's COVID-19 Government Response Tracker (OxCGRT) [17]. Policy stringency is a composite measure of anti-contagion policy strength calculated from nine indicators, including, but not limited to, the stringency of travel bans, school closures, and business closures, with each indicator ranging from 0 (least stringent) to 100 (most stringent). Dergiades et al. tested for a break in the slope of the time-series mortality rate data for each country, as changes in slope affect the method in which the time-series data is modeled and estimated. Autoregressive models, types of time-series forecasting models, were then applied to predict the trend of mortality rates in the countries studied. Probit regression, a model for dichotomous

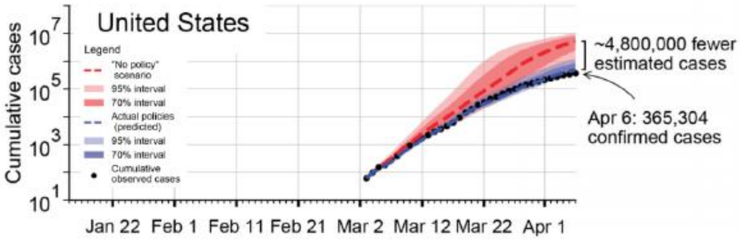

Fig. 2: Estimated cumulative confirmed COVID-19 infections with and without anti-contagion policies in the United States. A no policy scenario in the U.S. is predicted to lead to a 4.8 million increase in COVID-19 cases [3].

variables, was utilized to estimate the probability of attaining an insignificant trend slope for death rate, given the policy stringency index of a country. The study's results indicate that countries with higher stringency indices have a higher probability of attaining a trend slope of 0 (i.e. insignificant increase in death rate), and that increases in policy strength lead to a decrease in the average growth rate of deaths (Fig. 3).

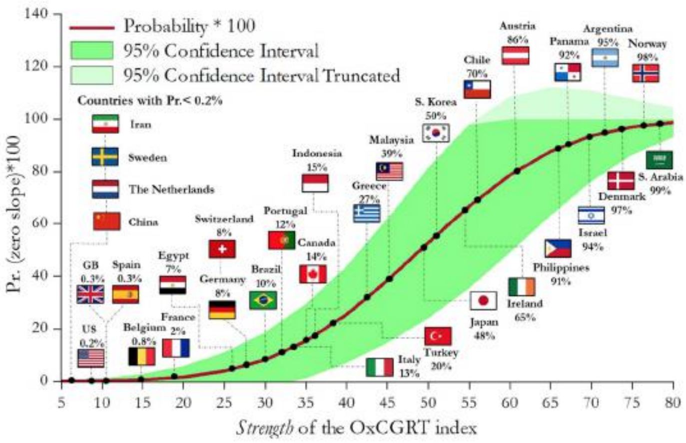

Fig. 3: Predicted probability of attaining an insignificant death rate from a country's OxCGRT policy stringency index [7].

Current studies published on anti-contagion policy display the efficacy of country-level COVID-19 policies, which are gathered from publicly released COVID-19 anti-contagion policy data. However, to our knowledge, no studies have been published on state-level anti-contagion policies in the United States, potentially due to a lack of compiled data on state-level policy analysis.

3 Purpose

1. We aim to analyze the severity of U.S. state anti-contagion policies by analyzing Twitter tweets from state government Twitter accounts. Due to the accessibility of Twitter, many state governments use Twitter to broadcast COVID-19 guidelines. Severity is defined as the stringency of anti-contagion policy, reflected by the language used in government tweets.

2. We aim to evaluate the relation between policy severity and COVID-19 prevalence, hospitalization rate, and death rate by performing regression tests.

4 Methods

4.1 Data Collection

To create a corpus relevant to individual U.S. state anti-contagion policies, we gather past Twitter tweets from U.S. state government accounts using Tweepy, a Python package for Twitter data mining. We acquire 149,633 tweets posted between August 7th, 2018 and July 18th, 2020 from 50 U.S. state government accounts that are labeled with the account handle, the U.S. state in which the account handle corresponds to, and the tweet date. The accounts are primarily individual state health department Twitter handles, but also include governor accounts for states that lack an active state health department Twitter account. The list of Twitter handles is included in Appendix A.

4.2 Data Preprocessing

We preprocess the tweets in five steps: 1) filter out tweets posted before March 1st, 2020, 2) standardize common COVID-19 phrases, 3) normalize the corpus, 4) perform lemmatization, and 5) remove stopwords. Tweets posted before March 1st, 2020 do not pertain to COVID-19 and are removed accordingly. Common COVID-19 related words are standardized into a single form (e.g. replacing $COVID$-19, $coronavirus$, $corona\,virus$, etc. with $covid$; replacing 6 $feet$, 6 ft, $six\ ft$, etc. with $six\ feet$) to reduce unnecessary variation. Normalization consists of removing duplicate tweets, converting the corpus to lowercase, removing URLs and user tags, and removing special characters and numbers. Lemmatization, the process of reducing an inflected form of a word to its base form (e.g. $infecting$ to $infect$), is performed using the spaCy library's $en\_core\_web\_sm$ model. Finally, we remove stopwords using a stopword list we define, due to pre-defined stopword lists removing words significant to tweet severity (e.g. $do\,not$). The stopword list is included in Appendix A.

4.3 Topic Labeling of Tweets

After data preprocessing, 40,327 tweets remain in the corpus. To eliminate remaining tweets unrelated to anti-contagion policy, we implement a two-phase topic modeling feature selection approach. Two topic models are used to filter out all irrelevant tweets, since tweets unrelated to anti-contagion policy remain after implementing only a single LDA model. We utilize Latent Dirichlet Allocation via the Gensim LDA Mallet package to cluster tweets into their primary topics. Both topic models are optimized by fine-tuning T, the number of topics, to maximize the coherence score of the model. For the first model, we find that a T of 24 topics yields the highest coherence score (Fig. 4). Based on the dominant keywords generated for each topic, we filter out topics that do not pertain to anti-contagion policies, reducing the corpus size to 15,170 tweets. For the second model, we find that a T of 15 topics yields the highest coherence score (Fig. 5). After filtering out topics which do not pertain to anti-contagion policies, we reduce the corpus size to 6,410 tweets. The list of topics for both models can be found in Appendix B.

4.4 Document Training Set Generation

To create a training set of documents, we define three classes: $severe$, $moderate$, and $not\,severe$. We randomly select a subset of 200 tweets, and we hand label each tweet with a class. From this labeled subset of tweets, we manually find keywords that are indicative of a tweet's severity level to create a list of keywords for each severity class. We use WordNet, a lexical database which organizes nouns, verbs, and adjectives into sets of synonyms, to obtain synonyms for the initial list of keywords in order to expand our keyword list. The list of keywords is found in Appendix B. The spaCy PhraseMatcher algorithm is used to create the training set of documents, which is defined as tweets containing three or more keywords from one of the three defined classes. In total, the training corpus consists of 194 tweets labeled $moderate$, 439 tweets labeled $not\,severe$, and 236 tweets labeled $severe$.

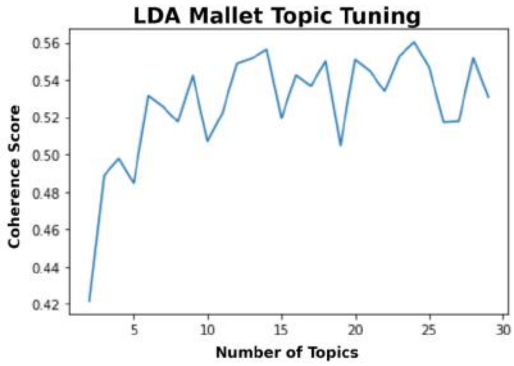

Fig. 4: Phase 1 T tuning of LDA model. 30 models are created with T values ranging from 1 to 30, and a coherence score is calculated for each model. We find that a T value of 24 yields the highest coherence score.

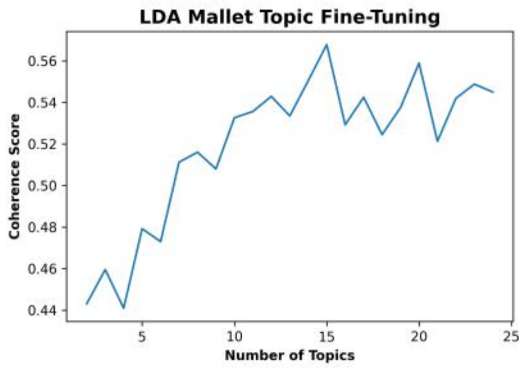

Fig. 5: Phase 2 T tuning of LDA model. 25 models are created with T values ranging from 1 to 25, and a coherence score is calculated for each model. We find that a T value of 15 yields the highest coherence score.

4.5 Tweet Classification

We first utilize the Gensim library to train a Word2vec model on the tweet corpus, generating word embeddings for each tweet. As per convention, a dimension size of 100 is chosen for the word embeddings [15]. To determine the optimal classification model, we train five models on the training corpus using the Scikit-Learn library's: 1) random forest ensemble model, 2) Naive-Bayes model, 3) K-nearest neighbors model, 4) logistic regression model, and 5) support vector machine. The random forest model is optimized by fine-tuning $n\text{–}estimators$, the number of trees in the random forest ensemble, with an $n\text{–}estimator$ value of 7 being chosen (Fig. 6). The K-nearest neighbors model is optimized by fine-tuning k, the number of nearest neighbors, with a k value of 4 being chosen (Fig. 7). The Naive-Bayes model, logistic regression model, and support vector machine model do not require hyperparameter tuning.

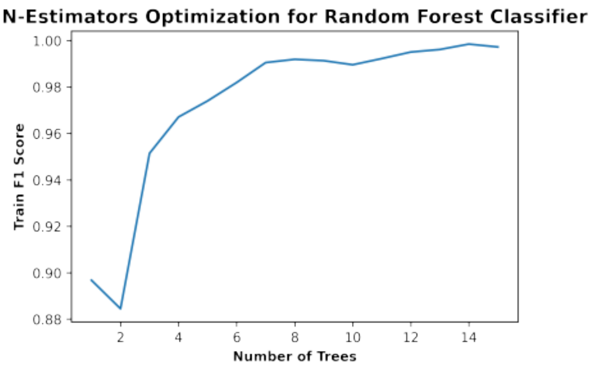

Fig. 6: $N - estimators$ tuning for random forest classifier. A macro-averaged F_1 score (calculated on the training corpus) is obtained for each $n - estimator$. We find an $n - estimator$ value of 7 to be optimal, with values greater than 7 having minimal effects on the F1 score, and thereby potentially over-fitting on the training corpus.

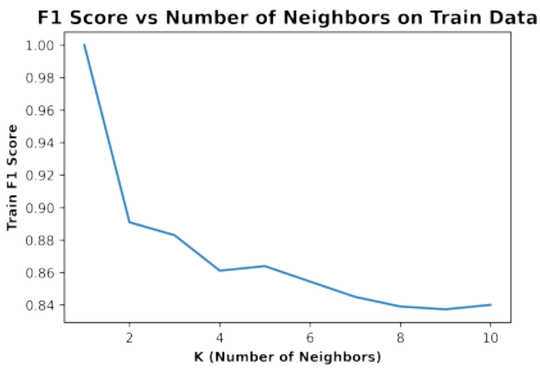

Fig. 7: K hyperparameter tuning for K-Nearest Neighbors classifier. A macro-averaged F_1 score (calculated on the training corpus) is obtained for each k value. Using the elbow methodology [18], we find a k value of 4 to be optimal.

We determine the optimal classification model by calculating a macro-averaged F_1 score from the predicted labels each model generates on the training corpus and the true labels of the training corpus. Confusion matrices for each classification model are found in Appendix B. We find that the random forest model is the optimal model, generating the highest F_1 score of 0.990 (Table 1).

Model	$\mathbf{F_1}$
K-Nearest Neighbors	0.869
Logistic Regression	0.827
Naive-Bayes	0.701
Random Forest	0.990
Support Vector Machine	0.827

Tab. 1: Macro-averaged F_1 scores for each classification model, calculated from the predicted tweet labels of the training corpus and the true labels of the training corpus.

4.6 Regression Analysis

We gather epidemiological data from March 1, 2020 to July 18, 2020, from the COVID Tracking Project, an API containing information on COVID-19 statistics from each U.S. state [19]. We use each state's cumulative case count, cumulative hospitalization count, and cumulative death count, as of July 18, 2020, to calculate the prevalence, hospitalization rate, and mortality rate, respectively. Per the Centers for Disease Control and Prevention's definitions of epidemiology measures, prevalence is defined as $\frac{\text{Cumulative Case Count}}{\text{Population Size}} \times 100$. Hospitalization rate is defined as $\frac{\text{Cumulative Hospitalization Count}}{\text{Population Size}} \times 1000$. Mortality rate is defined as $\frac{\text{Cumulative Death Count}}{\text{Population Size}} \times 1000$ [20]. To analyze a state's policy severity, we define a numerical scale for tweet severity: $severe$ tweets are assigned a value of 2, $moderate$ tweets are assigned a value of 1, and $not\ severe$ tweets are assigned a value of 0.

We complete a regression analysis for four sets of the data: 1) cumulative policy severity and COVID-19 measures for all 50 states, 2) cumulative policy severity and COVID-19 measures for the 20 U.S. states with the largest population density, 3) cumulative policy severity and COVID-19 measures for states with at least 100 anti-contagion policy related tweets (totaling to 18 states), and 4) monthly policy severity and COVID-19 measures for states with at least 100 anti-contagion policy related tweets.

4.6.1 Cumulative Policy Severity and COVID-19 Measures For 50 States

We first analyze cumulative data from all 50 states to investigate the overall relation of policy severity assign every state a mean policy severity score by averaging the severity values of each state's tweets. We then calculate the strength of a correlation between a state's policy severity and prevalence, hospitalization rate, and mortality rate by fitting a least squares regression line on the data, then calculating the coefficient of determination and Pearson correlation coefficient of the regression. A regression with hospitalization rates with rates of zero removed is also performed since some rates of zero are possibly due to the state having less COVID-19 testing kits; the COVID Tracking Project defines hospitalization counts as the number of patients who have tested positive for COVID-19, and it's possible that certain states have reported lower hospitalization counts due to a lower availability or delay of testing results [19].

4.6.2 Cumulative Policy Severity and COVID-19 Measures For 20 States With Highest Densities

To eliminate the potential effect of state density on policy severity, thereby affecting the correlation between policy severity and COVID-19 measures, we complete linear regression analyses on the 20 U.S. states with the highest population densities. We calculate the strength of a correlation between policy severity and prevalence, hospitalization rate, and mortality rate.

4.6.3 Cumulative Policy Severity and COVID-19 Measures For States With Highest Tweet Volume

To eliminate the potential inaccuracy of a state's policy severity due to low tweet volumes, we perform regression on states with a tweet volume of 100 or more anti-contagion policy tweets, accounting for 18 total states (see Appendix C for individual state tweet counts). We calculate the strength of a correlation between policy severity and prevalence, hospitalization rate, and mortality rate.

4.6.4 Monthly Policy Severity and COVID-19 Measures For States With Highest Tweet Volume

We examine the relation between changes in policy severity and COVID-19 measures by analyzing tweet severity on a monthly scale. To reduce potential inaccuracies due to low tweet volumes, we analyze only states with a tweet volume of 100 or more tweets. We divide the tweets (spanning from March 1, 2020 to July 18, 2020) into five groups of 28 days each: 1) March 1 to March 28, 2) March 29 to April 25, 3) April 26 to May 23, 4) May 24 to June 20, and 5) June 21 to July 28. We calculate the average policy severity score, prevalence, hospitalization rate, and death rate for each state during each time frame. The data for the 5 time frames is then combined for regression to be performed, and the coefficient of determination and Pearson correlation coefficient is calculated.

5 Results

5.1 U.S. State Policy Severity

Figure 8 shows the mean anti-contagion policy severity score for U.S. states, rounded to four decimal places. Of all 50 states, Michigan has the highest policy severity score of 0.7037, while Kentucky has the lowest policy severity score of 0.1053. Table 2 shows the total number of tweets belonging to each severity class.

Severity Class	Number of Tweets
Not Severe	4,213
Moderate	1,244
Severe	953

Tab. 2: Total number of tweets in each severity class.

Of the 6,410 tweets in the tweet corpus, 66% of the tweets are classified as not severe, 19% of the tweets are classified as moderate, and 15% of the tweets are classified as severe. Specific counts of tweets by individual states are found in Appendix C.

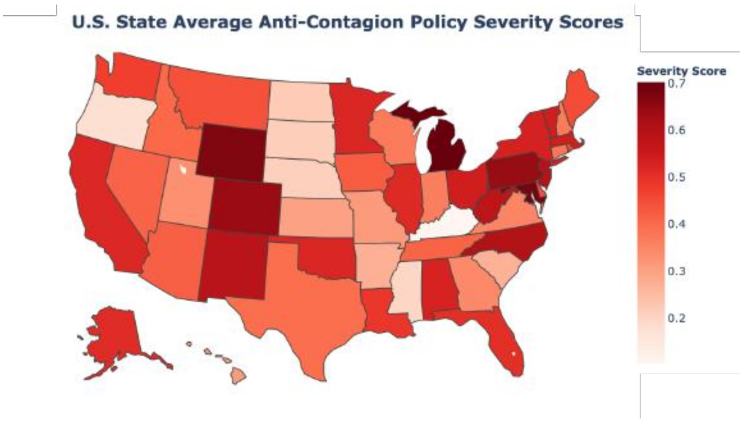

Fig. 8: Mean anti-contagion policy severity score from March 1, 2020 to July 18, 2020, calculated for U.S. states.

5.2 Policy Severity and COVID-19 Epidemiological Data Correlation

5.2.1 Cumulative Policy Severity and COVID-19 Measures For 50 States

Linear regression is performed on the average policy severity of each U.S. state versus the prevalence, hospitalization rate, and mortality rate (Fig. 9, 10, 11, 12). For hospitalization rate, linear regression is first performed for all 50 states, then performed on states with hospitalization rates greater than zero. Table 3 shows the Pearson's correlation coefficient for each linear regression.

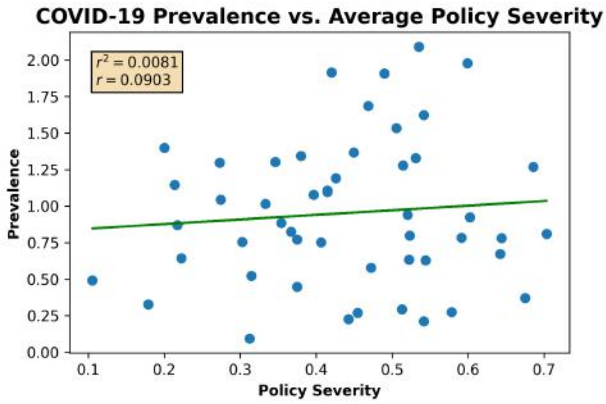

Fig. 9: COVID-19 prevalence vs. average policy severity for all U.S. states. Prevalence is calculated from the cumulative number of cases as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

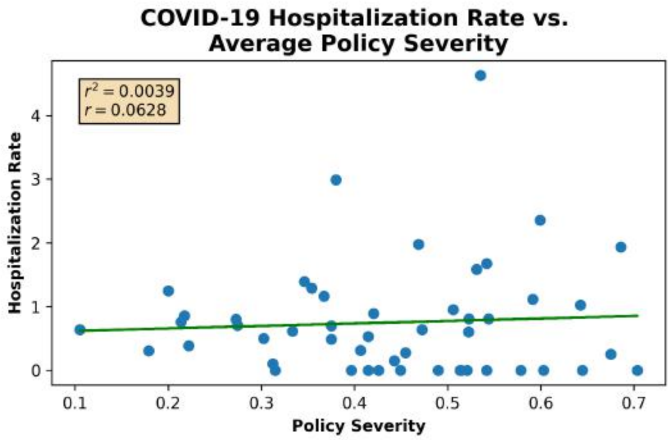

Fig. 10: COVID-19 hospitalization rate vs. average policy severity for all U.S. states. Hospitalization rate is calculated from the cumulative number of hospitalizations as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

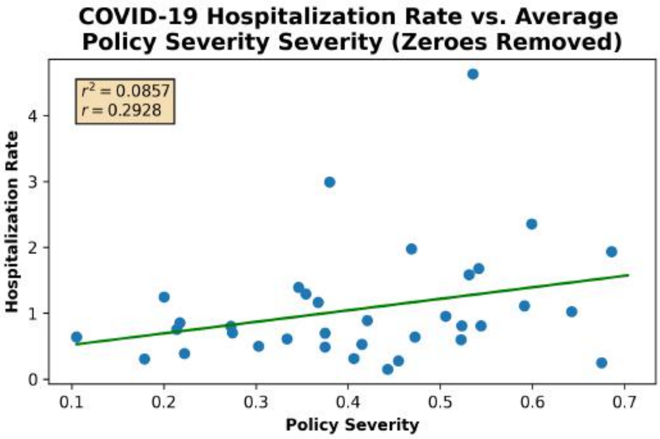

Fig. 11: COVID-19 hospitalization rate vs. average policy severity for all U.S. states, with hospitalization rates of zero removed. Hospitalization rate is calculated from the cumulative number of hospitalizations as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

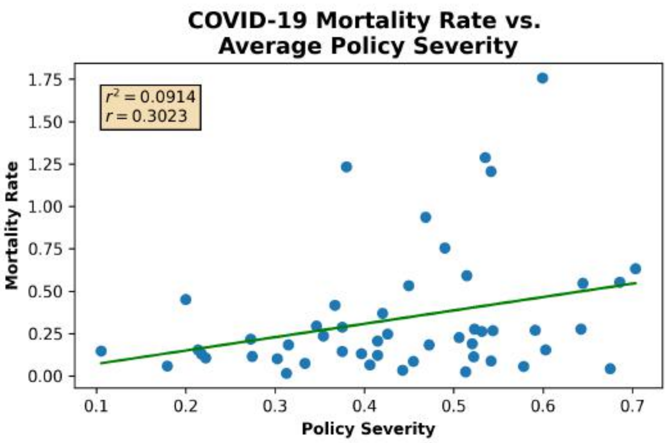

Fig. 12: COVID-19 mortality rate vs. average policy severity for all U.S. states. Mortality rate is calculated from the cumulative number of deaths as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

Linear Regression Model	**Pearson's r**
Prevalence vs. Severity	0.0903
Hospitalization Rate vs. Severity	0.0628
Hospitalization Rate vs. Severity (Zeroes Removed)	0.2928
Mortality Rate vs. Severity	0.3023

Tab. 3: Pearson correlation coefficients (r) for each linear regression model.

All four regressions display positive correlation coefficients. Prevalence, as well as hospitalization rate, have correlation coefficients around 0.08. Hospitalization rate with rates of zero removed, as well as mortality rate, have correlation coefficients around 0.3.

5.2.2 Cumulative Policy Severity and COVID-19 Measures For 20 States With Highest Densities

Linear regression is performed on the average policy severity of the U.S. states with the 20 highest population densities, versus the prevalence, hospitalization rate, and mortality rate (Fig. 13, 14, 15). Table 4 shows the Pearson's correlation coefficient for each linear regression.

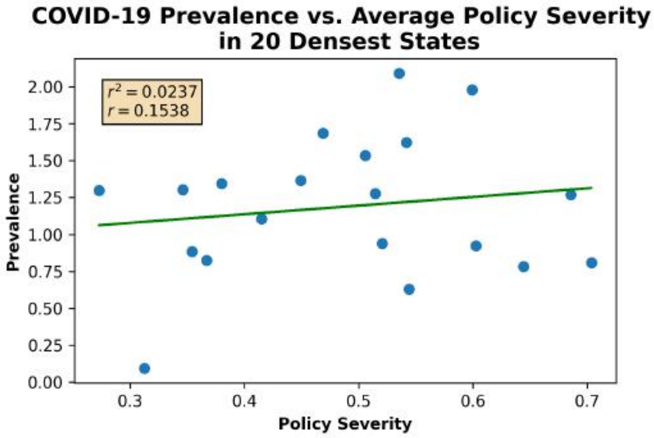

Fig. 13: COVID-19 prevalence vs. average policy severity for U.S. states with 20 highest population densities. Prevalence is calculated from the cumulative number of cases as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1st, 2020 to July 18, 2020.

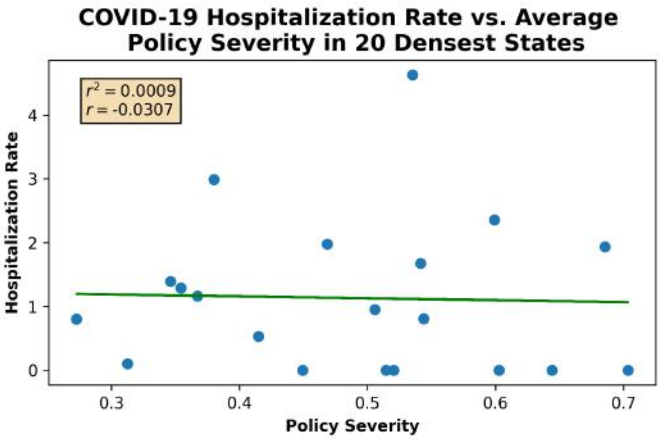

Fig. 14: COVID-19 hospitalization rate vs. average policy severity for U.S. states with 20 highest population densities. Hospitalization rate is calculated from the cumulative number of hospitalizations as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

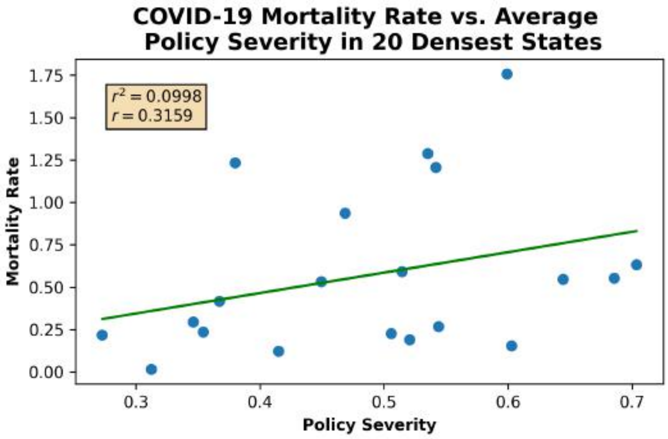

Fig. 15: COVID-19 mortality rate vs. average policy severity for U.S. states with 20 highest population densities. Mortality rate is calculated from the cumulative number of deaths as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

Linear Regression Model	**Pearson's *r***
Prevalence vs. Severity	0.1538
Hospitalization Rate vs. Severity	-0.0307
Mortality Rate vs. Severity	0.3159

Tab. 4: Pearson correlation coefficients (r) for each linear regression model.

The regressions for prevalence and mortality display positive correlation coefficients, while the regression for hospitalization rate displays a negative correlation coefficient. Prevalence and mortality rate exhibit weak correlations with policy severity, and hospitalization rate exhibits no correlation with policy severity.

5.2.3 Cumulative Policy Severity and COVID-19 Measures For States With Highest Tweet Volume

Linear regression is performed on the average policy severity of the U.S. states with tweet volumes of 100 or more tweets, versus the prevalence, hospitalization rate, and mortality rate (Fig. 16, 17, 18). Table 5 shows the Pearson's correlation coefficient for each linear regression.

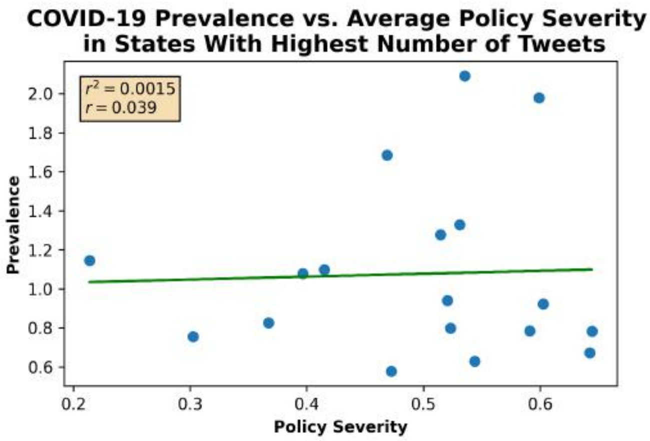

Fig. 16: COVID-19 prevalence vs. average policy severity for U.S. states with tweet volumes of 100 or more tweets. Prevalence is calculated from the cumulative number of cases as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

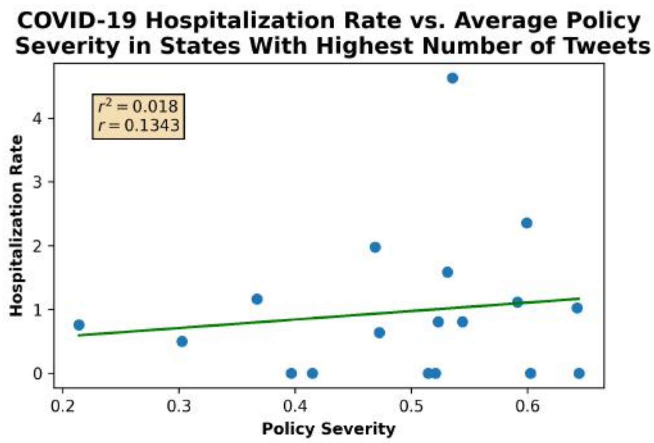

Fig. 17: COVID-19 hospitalization rate vs. average policy severity for U.S. states with tweet volumes of 100 or more tweets. Hospitalization rate is calculated from the cumulative number of hospitalizations as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

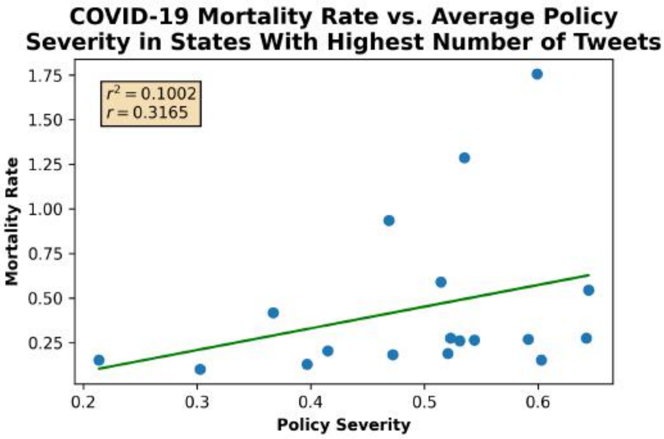

Fig. 18: COVID-19 mortality rate vs. average policy severity for U.S. states with tweet volumes of 100 or more tweets. Mortality rate is calculated from the cumulative number of deaths as of July 18, 2020. Severity is calculated as the mean tweet severity of anti-contagion policy tweets from March 1, 2020 to July 18, 2020.

Linear Regression Model	**Pearson's r**
Prevalence vs. Severity	0.0390
Hospitalization Rate vs. Severity	0.1343
Mortality Rate vs. Severity	0.3165

Tab. 5: Pearson correlation coefficients (r) for each linear regression model.

All three regressions display positive correlation coefficients. Hospitalization rate and mortality rate exhibit weak correlations with policy severity, and prevalence exhibits no correlation with policy severity.

5.2.4 Monthly Policy Severity and COVID-19 Measures For States With Highest Tweet Volume

Linear regression is performed on the monthly average policy severity of the U.S. states with tweet volumes of 100 or more tweets, versus the prevalence, hospitalization rate, and mortality rate (Fig. 19, 20, 21). Table 6 shows the Pearson's correlation coefficient for each linear regression.

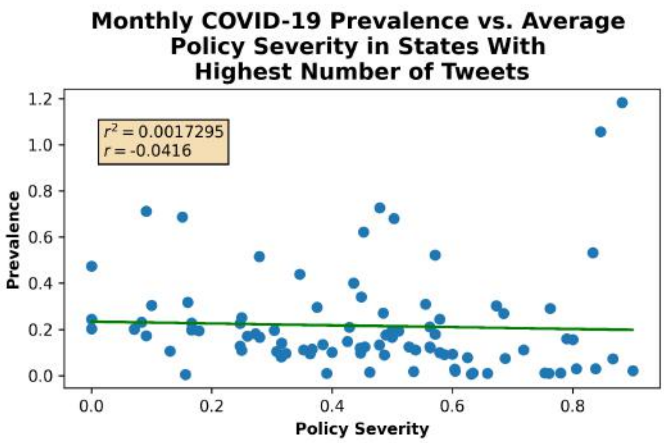

Fig. 19: COVID-19 prevalence vs. monthly average policy severity for U.S. states with tweet volumes of 100 or more tweets. Prevalence is calculated as the cumulative number of cases per 28 days. Severity is calculated as the mean tweet severity of anti-contagion policy tweets per 28 days.

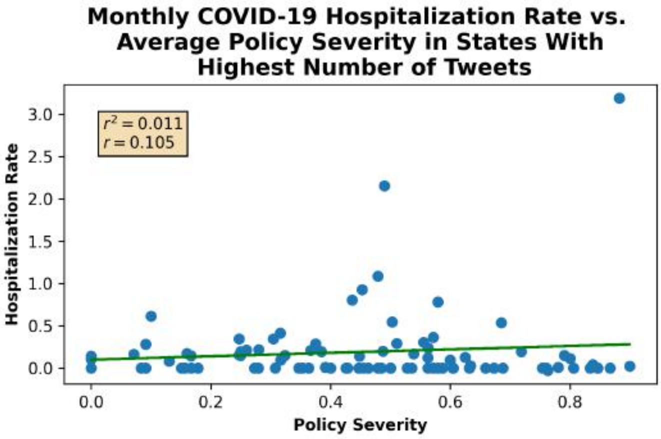

Fig. 20: COVID-19 hospitalization rate vs. monthly average policy severity for U.S. states with tweet volumes of 100 or more tweets. Hospitalization rate is calculated from the cumulative number of hospitalizations per 28 days. Severity is calculated as the mean tweet severity of anti-contagion policy tweets per 28 days.

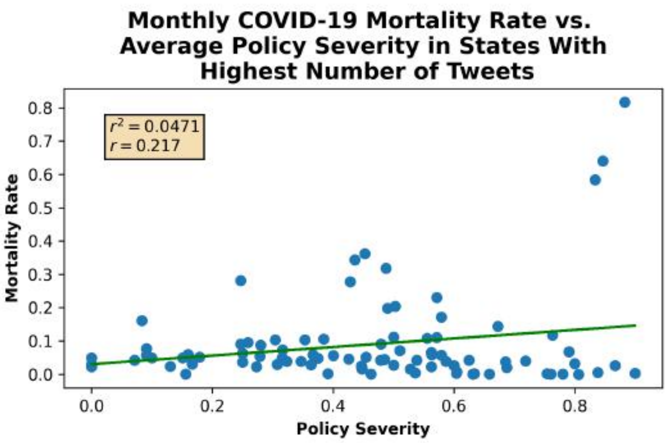

Fig. 21: COVID-19 mortality rate vs. monthly average policy severity for U.S. states with tweet volumes of 100 or more tweets. Mortality rate is calculated from the cumulative number of deaths per 28 days. Severity is calculated as the mean tweet severity of anti-contagion policy tweets per 28 days.

Linear Regression Model	**Pearson's r**
Prevalence vs. Severity	-0.0416
Hospitalization Rate vs. Severity	0.1050
Mortality Rate vs. Severity	0.2170

Tab. 6: Pearson correlation coefficients (r) for each linear regression model.

The regressions for hospitalization rate and mortality rate display positive correlation coefficients, while the regression for prevalence displays a negative correlation coefficient. Hospitalization rate and mortality rate exhibit weak correlations with policy severity, and prevalence exhibits no correlation with policy severity.

6 Discussion

In our first set of regressions, we analyze the average policy severity and COVID-19 measures of all 50 U.S. states. For these analyses, both the regression of prevalence against severity, as well as the regression of hospitalization rate against severity, display correlation coefficients less than 0.10, indicating that there is no linear relation between these two variables and severity. This is perhaps because while some smaller, sparser states with a low amount of cases tend to implement less severe policies due to their lack of need for stricter policies, larger states that also have less severe policies might have much higher case counts and hospitalization rates. Additionally, the lack of correlation between the hospitalization rates and severity for all 50 states can possibly be attributed to variations in the quality of healthcare systems and COVID-19 testing availability for each state. Several states with varying levels of policy severity all exhibit hospitalization rates close to zero, which may be due to these states having less hospital availability or having less COVID-19 testing kits; the COVID Tracking Project defines hospitalization counts as the number of patients who have tested positive for COVID-19, so it's possible that certain states have reported lower hospitalization counts due to a lower availability of testing results [19].

Once hospitalization rates of zero are removed, the regression between the remaining hospitalization rates and policy severity has a correlation coefficient of 0.30, indicating a moderately weak, positive correlation. Since the severity score used in this regression is taken as an average of all severity scores over a 4 month time frame, and the hospitalization rate is taken over the cumulative hospitalizations, it is possible that states that started with less severe policies experienced many hospitalizations in the first months of the pandemic, thereby increasing their hospitalization rate, and as a result, implemented stricter anti-contagion policies, raising their severity score. The regression between mortality rate and policy severity has a correlation coefficient of 0.29, indicating a moderately weak, positive correlation. Surprisingly, the positive correlation between mortality rate and policy severity is opposite the findings of Dergiades et al., who found that increases in policy severity lead to a decrease in mortality rates [7]. One potential explanation is that while Dergiades et al. conducted time-series analyses of mortality rates and policy severity, this regression did not account for changes in policy severity and mortality rate over time. Similar to the regression of hospitalization rates (with zeros removed), a possibility is that states which originally had less severe policies experienced high death rates in the first months of the pandemic, and increased their anti-contagion policy severity in response, raising their average severity score.

In our second set of regressions, we analyze the average policy severity and COVID-19 measures of the 20 U.S. states with the highest population densities. By analyzing only states with the highest population densities, we minimize inconsistencies in tweet severity caused by variations in population density. For these analyses, the regression of hospitalization rate against severity displays a negative correlation coefficient of -0.0307 with an absolute value less than 0.01, indicating that there appears to be no linear relation between hospitalization rate and severity for these states. As mentioned previously, the lack of correlation is potentially due to variations in testing availability and inconsistencies among states in defining COVID-19 hospitalization counts.

The regressions for prevalence and mortality rate exhibit correlation coefficients of 0.15 and 0.32, respectively, indicating there exists a moderately weak, positive relationship between prevalence and mortality rate with policy severity. The positive correlations are at odds with the findings of Dergiades et al. and Hsiang et al. [7, 3], and as mentioned previously, a potential explanation is that these regressions did not account for changes in policy severity over time, causing the trends in the data to differ from the studies of Dergiades et al. and Hsiang et al.

In the third set of regressions, we analyze the average policy severity and COVID-19 measures of U.S. states with tweet volumes of at least 100 tweets in order to reduce inaccurate policy severity values caused by low tweet volumes. In these analyses, the regression of prevalence against severity displays a correlation coefficient less than 0.0390, indicating no linear relationship between tweet severity and prevalence. The regressions of hospitalization rate and mortality rate against policy severity display positive, moderately weak correlation coefficients of 0.13 and 0.32, respectively. Again, these trends contrast with the findings of previous studies, and this may be attributed to the fact that this set of regressions does not account for the effects that variations in population density may have on policy severity.

In the last set of regressions, we analyze the monthly policy severity of the U.S. states with tweet volumes of 100 or more tweets. By performing regression on the monthly average policy severity rather than the overall mean policy severity, we can evaluate the impacts that changes in policy may have on COVID-19 epidemiological data. We find that the regression of prevalence against severity displays a negative correlation coefficient of -0.04, signifying that there is no linear relationship between prevalence and severity. Similar to the previous regressions, this is perhaps due to the effect that state density may have on prevalence: states with lower densities experience low person-to-person to contact and therefore low disease transmission, and these states may implement less stringent anti-contagion policies. At the same time, some larger states with higher prevalence possibly do not implement stringent policies either, and this causes the regression to appear as if there is no correlation between prevalence and policy severity.

The regressions of hospitalization rate and mortality rate exhibit correlation coefficients of 0.11 and 0.22, indicating that these two variables have positive, weak correlations with policy severity. Again, these results contrast from the studies of Dergiades et al. and Hsiang et al., who found that higher policy stringencies have a negative correlation with mortality and hospitalization rate. One probable explanation for these results is that although the data used in this set of regressions was calculated over monthly intervals, Dergiades et al. and Hsiang et al.'s studies analyzed COVID-19 data on a daily scale, allowing the studies to have a higher degree of specificity and a more accurate reflection of COVID-19 trends. Furthermore, since our regressions were performed on monthly data, it is possible that states which experienced high hospitalization rates or mortality rates in a month implemented more stringent COVID-19 policies, and once these rates decreased, the states lowered the stringency of the anti-contagion policies, decreasing the monthly policy severity score and thereby resulting in a positively correlated trend.

Finally, it is probable that each calculated severity score is not reflective of the state's policy severity, leading to unrepresentative regression results. This can be attributed to several reasons, including that low tweet volumes were obtained for many states, and government handles could potentially be inclined to use more positive language when communicating through Twitter, causing the tweet severity score to inaccurately represent the state's stringency of anti-contagion policies.

7 Conclusion

In this work, we present a method to analyze U.S. anti-contagion policy severity from U.S. state government Twitter tweets based on a random forest classification approach. We show that our method can be used to classify a state's guideline severity and quantify the relation of guideline severity with COVID-19 epidemiological data on a state-level scope. We measure the correlation strength between tweet severity and COVID-19 prevalence, hospitalization rate, and death rate for U.S. states, showing that policy severity and COVID-19 epidemiology data have moderately weak, positive correlations. These are preliminary results, and more analysis on patterns between policy severity and epidemiological data is necessary to predict the effect of policy severity on COVID-19 measures. Through additional time-series modeling of policy severity and COVID-19 data, as well as other influential factors such as testing availability, infection and mortality measures can be predicted from various anti-contagion policies. If the efficacy of U.S. anti-contagion policies can be modeled, governments on local, state, and even national levels can use such findings to implement strategically designed approaches to combating the COVID-19 pandemic.

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Appendix A

State	Twitter Account
Alabama	ALPublicHealth
Alaska	Alaska_DHSS
Arizona	AZDHS
Arkansas	ADHPIO
California	CAPublicHealth
Colorado	CDPHE
Connecticut	CTDPH
Delaware	Delaware_DHSS
Florida	HealthyFla
Georgia	GaDPH
Hawaii	HIgov_Health
Idaho	IDHW
Illinois	IDPH
Indiana	StateHealthIN
Iowa	IAPublicHealth
Kansas	KDHE
Kentucky	KYHealthAlerts
Louisiana	LADeptHealth
Maine	MEPublicHealth
Maryland	MDHealthDept
Massachusetts	MassDPH
Michigan	MichiganHHS
Minnesota	mnhealth
Mississippi	msdh
Missouri	HealthyLivingMo
Montana	GovernorBullock
Nebraska	NEDHHS
Nevada	NVHealthRespon1
New Hampshire	NHPubHealth
New Jersey	NJDeptofHealth
New Mexico	NMDOH
New York	HealthNYGov
North Carolina	ncdhhs
North Dakota	NDDOH
Ohio	OHdeptofhealth
Oklahoma	HealthyOklahoma
Oregon	OHAOregon
Pennsylvania	PAHealthDept
Rhode Island	RIHEALTH
South Carolina	scdhec
South Dakota	SDDOH
Tennessee	TNDeptofHealth
Texas	TexasDSHS
Utah	UtahDepOfHealth
Vermont	healthvermont
Virginia	VDHgov
Washington	WADeptHealth
West Virginia	WV_DHHR
Wisconsin	DHSWI
Wyoming	GovernorGordon

(a) **U.S. State Twitter Handles**

Stopwords	
a	on
about	once
above	only
after	or
again	other
against	our
am	ours
an	ourselves
and	out
any	over
are	own
as	pron
at	same
be	she
because	she's
been	so
before	some
being	such
below	than
between	that
both	the
but	their
by	theirs
can	them
down	themselves
during	then
each	there
few	these
for	they
from	this
further	those
he	through
her	to
here	too
hers	under
herself	until
him	up
himself	very
his	was
how	we
i	were
if	what
in	when
into	where
is	which
it	while
it's	who
its	whom
itself	why
just	will
me	with
my	you
myself	your
now	yours
of	yourself
off	yourselves

(b) **Stopword List**

Appendix B

Topic Number	Keywords	Number of Tweets	Included
0	test, site, covid, free, find	1667	Y
1	county, release, covid, phase, test	608	Y
2	hand, covid, wash, clean, spread	1083	Y
3	covid, symptom, test, people, home	1734	Y
4	food, supply, covid, donate, state	1510	Y
5	office, apply, online, eek, state	419	N
6	family, day, stayhomefornevada, time, lose	1860	N
7	covid, information, contact, question, health	2685	N
8	covid, live, update, watch, today	2607	N
9	test, report, covid, total, case	1276	N
10	covid, health, mental, support, child	2066	N
11	case, covid, datum, update, report	2320	N
12	school, wic, food, learn, student	976	N
13	wear, mask, face, covid, stay	3179	Y
14	risk, learn, condition, high, covid	1253	N
15	order, business, guidance, open, today	2483	Y
16	health, covid, work, public, worker	2079	N
17	stay, safe, tip, time, learn	1569	N
18	care, health, facility, child, covid	1417	N
19	case, covid, death, total, report	2326	N
20	covid, fund, census, business, federal	1183	N
21	covid, visit, patient, positive, information	420	N
22	covid, spread, state, continue, work	2955	Y
23	hospital, patient, covid, care, ventilator	652	N

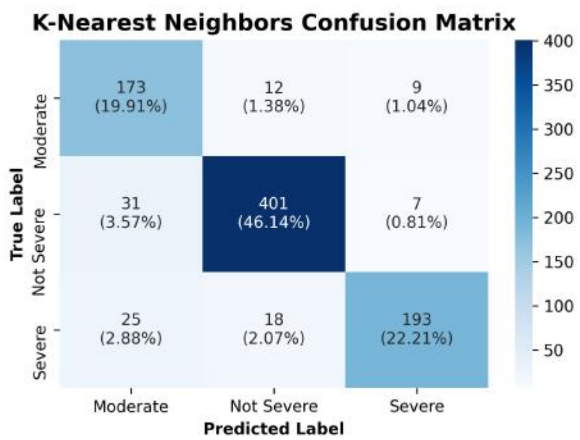
(c) **24 Topic Latent Dirichlet Allocation: List of Topics**

Topic Number	Keywords	Number of Tweets	Included
0	hand, wash, covid, clean, spread	1013	N
1	supply, ppe, mask, state, care	805	N
2	covid, case, spread, people, test	1146	N
3	business, essential, store, employee, service	890	Y
4	phase, reopen, plan, county, today	696	N
5	guidance, close, gathering, event, school	819	Y
6	covid, work, state, health, time	1578	N
7	stay, home, covid, spread, live	1157	Y
8	food, blood, covid, donate, bank	645	N
9	test, county, covid, free, health	699	N
10	test, site, covid, find, location	1246	N
11	wear, face, mask, cover, cloth	1455	Y
12	order, health, covid, state, travel	1013	Y
13	distance, social, stay, practice, covid	1076	Y
14	covid, symptom, provider, care, test	981	N

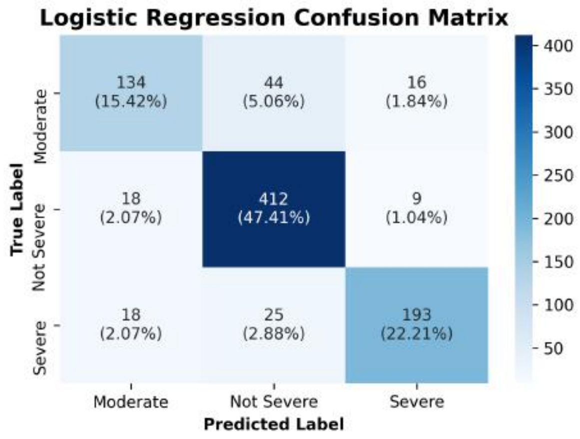
(d) **15 Topic Latent Dirichlet Allocation: List of Topics**

Severe	Moderate	Not Severe
critical	avoid	good idea
immediately	stay home	urge
immediate	do not	can take
right away	restrict	can help
a soon a possible	serious	recommend
must	seriously	encourage
require	minimize	discuss
need	vital	low risk
crucial	necessary	risk be low
terrible	essential	low risk
always	must	no risk
mandatory	close	will evaluate
order	always	evaluate
enforce	close down	fully prepare
prohibit	requisite	reconsider
stay at home order	prevent	limit travel
shut down	not optional	consider
shutdown		keep in mind
executive order		suggest
mandate		when possible
impose		if possible
dire		try to
ordain		permit
ban		volunteer
requirement		not require
		not enforce
		promote
		advise
		advocate
		discourage
		not close
		remain open
		optional

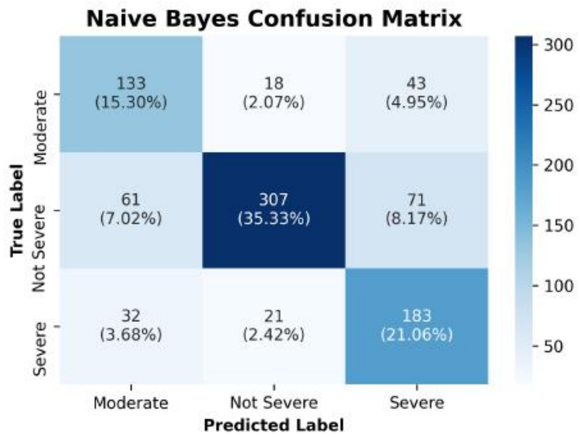
(e) **Severity Keywords**



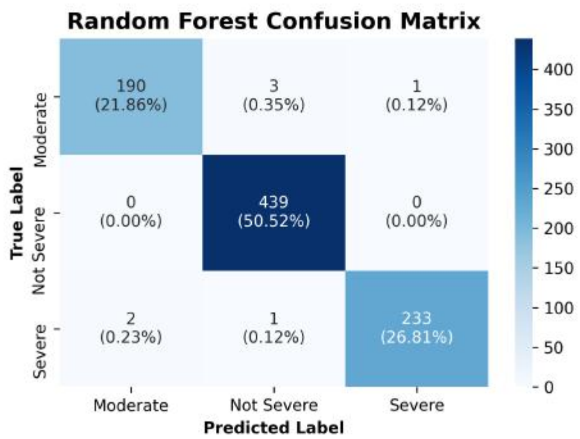
(f) **K-Nearest Neighbors Confusion Matrix**



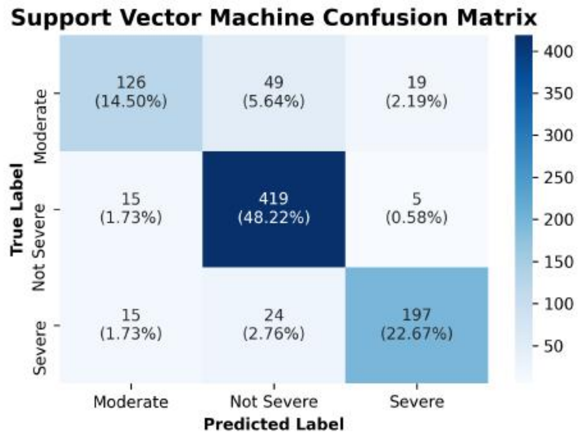
(g) **Logistic Regression Confusion Matrix**



(h) **Naive-Bayes Confusion Matrix**



(i) **Random Forest Confusion Matrix**



(j) **Support Vector Machine Confusion Matrix**

Appendix C

State	Severe Tweets	Moderate Tweets	Not Severe Tweets	Tweet Count
Alabama	53	22	166	241
Alaska	16	7	53	76
Arizona	7	23	58	88
Arkansas	6	2	43	51
California	26	49	119	194
Colorado	50	24	119	193
Connecticut	7	5	38	50
Delaware	13	14	62	89
Florida	16	12	59	87
Georgia	4	10	38	52
Hawaii	3	4	25	32
Idaho	9	8	47	64
Illinois	17	54	100	171
Indiana	22	14	122	158
Iowa	5	13	36	54
Kansas	14	8	97	119
Kentucky	0	2	17	19
Louisiana	14	20	64	98
Maine	2	1	8	11
Maryland	20	8	42	70
Massachusetts	2	9	13	24
Michigan	17	23	41	81
Minnesota	24	43	107	174
Mississippi	1	1	13	15
Missouri	7	3	44	54
Montana	3	21	37	61
Nebraska	10	8	113	131
Nevada	22	34	132	188
New Hampshire	10	4	50	64
New Jersey	48	43	141	232
New Mexico	21	78	104	203
New York	53	84	218	355
North Carolina	73	124	251	448
North Dakota	3	6	45	54
Ohio	70	64	241	375
Oklahoma	15	17	58	90
Oregon	3	6	58	67
Pennsylvania	52	146	190	388
Rhode Island	88	71	368	527
South Carolina	7	10	71	88
South Dakota	2	11	56	69
Tennessee	6	27	61	94
Texas	13	22	86	121
Utah	0	4	8	12
Vermont	11	17	44	72
Virginia	5	7	36	48
Washington	43	42	186	271
West Virginia	22	4	57	83
Wisconsin	7	10	47	64
Wyoming	11	5	24	40

(k) **State Tweet Counts By Severity Category**