ANALYZING THE EFFECTS OF DIFFERENT POLICIES AND STRICTNESS LEVELS ON MONTHLY CORONA VIRUS CASE INCREASE RATES USING MACHINE LEARNING AND BIG DATA ANALYSIS

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ABSTRACT

The corona virus is one of the most unprecedented events of recent decades. Countries struggled to identify appropriate COVID-19 policies to prevent virus spread effectively. Although much research has been done, little focused on policy effectiveness and their enforcement levels. As corona virus cases and death numbers fluctuated among countries, questions of which policies are most effective in preventing corona virus spread and how strict they should be implemented have yet to be answered. Countries are prone to making policy and implementation errors that could cost lives. This research identified the most effective policies and their most effective enforcement levels through data analysis of 12 common coronavirus policies. A monthly case increase rate prediction model was developed to enable decision makers to evaluate the effectiveness of COVID-19 policies and their enforcement levels so that they can implement policies efficiently to save lives, time, and money.

KEYWORDS

COVID-19 Policy Effectiveness, COVID-19 Policy Enforcement Level, COVID-19 Policy Enforcement Level and Effectiveness Consistency, Machine Learning Enabled Monthly COVID-19 Case Increase Rate Prediction.

1. INTRODUCTION

COVID-19 was first discovered in Wuhan, China, in December 2019. A cluster of pneumonia cases in the province was reported, and a novel coronavirus, later named COVID-19, was eventually identified. Coronavirus diseases are a large family of viruses that appear in humans and animals, spread through droplets and close contact, and cause mild to severe upper-respiratory-tract illnesses [1]. The two previous coronaviruses, MERS-CoV and SARS-CoV, had their origins from bats. Scientists linked the first coronavirus case in 2019 (COVID-19) to bats too. Although mild symptoms of COVID-19 are common and very similar to those of the flu, including fevers, coughs, and shortness of breath, COVID-19 is very deadly and has killed around 6.3 million people as of June 2022 [2]. In addition, a large amount of asymptomatic COVID-19 cases made it more difficult to track and prevent the spread of the virus. After experiencing the MERS and SARS pandemics, many people thought countries would have been more prepared to combat the current pandemic. However, lack of knowledge of COVID-19, delayed notice about the virus, opened borders for international travel, and mismanagement in handling the pandemic led to an exponential growth of cases in only a few months across the world. Effective policy implementation with appropriate enforcement could have prevented countries from reaching the current COVID-19 pandemic status, which has around 540 million

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cases and 6.3 million deaths worldwide as of June 2022 [2]. Although the vaccines from some companies (e.g. Pfizer, Moderna) have been approved by the FDA, countries will most likely still have to live with the virus for another year or more. Analyzing and identifying the most effective policies and their appropriate enforcement levels are critical because it is a matter of life and death, and trillion dollar economic impacts, and will also help the world be better prepared to handle future pandemics in an effective and timely manner before any approved vaccine is available to the world.

Some research that has been done to identify the most effective COVID-19 policies or predict COVID-19 cases utilize more advanced machine learning algorithms like Bayesian analysis [3] or Poisson regression [4]. However, most research do not account for the fact that these policies have various enforcement levels that affect the case rates. In addition, they have a narrower research scope, with some focusing only on the U.S. or on specific policy enforcement, which makes their research results only applicable to some countries' COVID-19 situations.

To address the gap in current research missing policy enforcement levels impact on policy effectiveness, this research tries to answer the question: "How effective and consistent are the policies and their enforcement levels implemented by different countries in preventing the spread of COVID-19?". This research defines Effectiveness as how much a policy implementation at a certain enforcement level can decrease the monthly case increase rate. Consistency is defined as whether the associated monthly case increase rate will decrease accordingly as a policy implementation strictness level increases (across all levels). This research analyzed the policy consistency and effectiveness separately first. To measure policy effectiveness, a machine learning model with a linear regression algorithm was developed. If the resulting coefficient of the corresponding policy was negative, it meant that the policy helped decrease the monthly case rate; if the coefficient was positive, it meant the policy instead led to the increase of monthly case rates. To measure policy enforcement level consistency, Google Sheets was utilized to create graphs for each policy and identified whether the monthly case increase rate decreased as the policy enforcement level increased. Then the research integrated the policies' effectiveness and consistency analysis results to categorize the 13 policies into three overall effectiveness tiers - most effective, partly effective, and not effective.

The machine learning model code was run 50 times and outputted the machine learning model with the highest accuracy. The accuracy was evaluated using R-Squared, which is a representation of how well the model fits the dataset [5]. The R-Squared of the model used in the research was around 19%. Though it may seem relatively low, it is not bad because this research is related to human behavior. Since human behavior is very hard to be exactly predicted, machine learning models related to human behavior usually have lower R-Squared values. Furthermore, the policies identified in the most effective category not only have a negative coefficient to the policy's enforcement level in the monthly case increase rate prediction model, but also show consistency in their enforcement levels per the graphs.

The rest of the paper is organized as follows: Section 2 briefly discusses the challenges encountered during research and experimentation; Section 3 illustrates the solutions to find the answer to the research question and resolve challenges; Section 4 presents relevant details about the experiments done. Section 5 presents related research. Finally, Section 6 gives concluding remarks, as well as discussing future work of this project.

2. CHALLENGES

A list of major technical challenges encountered in this project are presented as follows:

2.1. Challenge 1: The Handling of the Incomplete Dataset Values

The data was collected from ourworldindata.org. It included policy enforcement level and COVID-19 case numbers from 180 countries around the world from January 2020 to November 2020 (at the time of the start of this research). After downloading the data, a major observation was that there were some null values. This could be because some underdeveloped countries did not have the resources to collect and provide their COVID-19 case numbers, or because some countries had not even begun to monitor COVID-19 at the time. Null values make it difficult to develop an appropriate machine learning model. It was important for the research to address the null value data challenge.

2.2. Challenge 2: Insufficiency of the Dataset for Calculations

In the research dataset, a column called "Monthly Case Increase Rate" was added. The formula for this column is (Month 2's Total Cases - Month 1's Total Cases) / Month 1's Total Cases. The resulting increase rate would be placed as Month 1's Monthly Case Increase Rate. However, there was a problem when the data went from the last month (e.g., November 2020) of a country, to the first month (e.g., April 2020) of the next country. In the scaled-down data set, there was no data for December 2020 that could be used to identify November 2020's monthly case increase rate.

2.3. Challenge 3: Integrating Two Research Analysis Results into Conclusions

The research was split into two analysis sections: policy enforcement level graphing for visualizing and analyzing the relationship between policy enforcement levels and monthly case increase rates and analyzing the developed machine learning model for monthly case increase rate predictions to identify a policy's effectiveness. The challenge was figuring out how to integrate results of the two analysis sections to evaluate the overall effectiveness of each policy in a quantitative and consistent way.

3. SOLUTION

3.1. Overview of the Solution

To answer the research question: "How effective and consistent are the policies and their enforcement levels implemented by different countries in preventing the spread of COVID-19?", the research established the hypothesis: If a country has a higher stringency index and enforces a higher level of strictness for each of the 12 policies listed in ourworldindata.org, then the monthly coronavirus case increase rate will decrease accordingly. The research takes the following approach (as shown in Figure 1): 1) Research and Identify Data Source; 2) Review, collect, and clean COVID-19 case data to finalize data across 168 countries in eight months for stringency index and 12 policies and their enforcement levels from ourworldindata.org; this addressed challenge #1 listed in section 2 by identifying the pattern of null data and removing them when having a minimum impact on overall data analysis; 3) Integrate, calculate, and analyze the data by using Google Sheets; this addressed challenge #2 listed in section 2 by setting the last month's case increase rate to that of the previous month; 4) Create graphs for stringency index and each policy's enforcement levels against the monthly coronavirus case increase rate to show their relationships by using Google Sheets; 5) Develop monthly case increase rate prediction model by using Google Colab and Python; and 6) Identify most effective policies and their enforcement level through quantitative data analysis of the graphs and the coefficients of the model. This addressed challenge #3 listed in section 2 by defining and calculating an effectiveness index integrating the consistency between a policy's enforcement level and monthly case decrease rate, with the policy's coefficient in the monthly case increase rate prediction model.

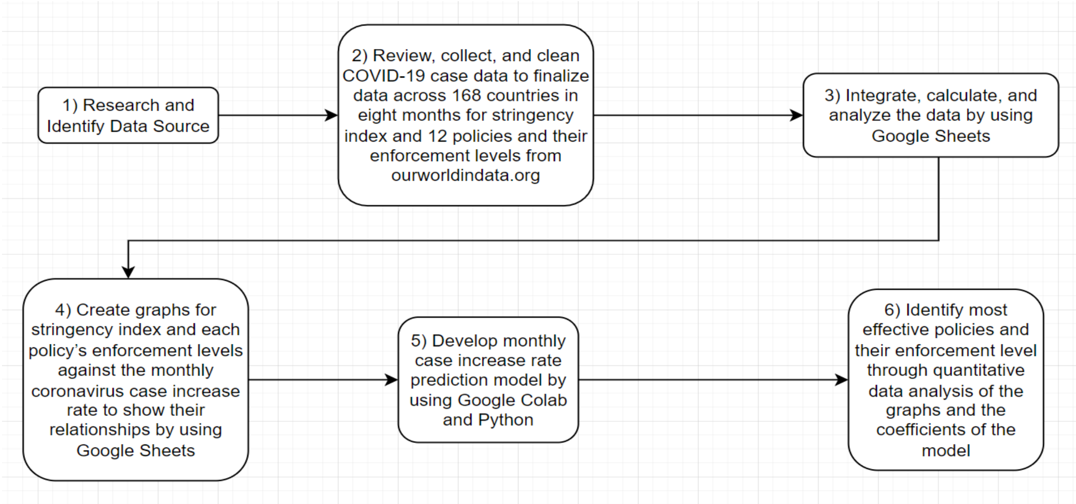


Figure 1. Overview of the Solution

3.2. Technical Details by Modules

First, ourworldindata.org was identified as the initial raw data, which has the enforcement levels of 12 COVID-19 policies and daily COVID-19 case numbers in 2020 across around 180 countries. Later, in 2021, the website added the 13th policy, Vaccinations. This research focused on the initial 12 major policies without the Vaccination Policy.

Second, the initial raw data across 180 countries was collected, cleaned, and integrated. When it came to null values in the data, the research analyzed the null data pattern and found that most null data were in the beginning three months of the dataset. This may be because some countries were not ready to collect data when COVID-19 just started. In addition, the research found that there were a couple of countries that did not have data in most of the months. This may be because those few countries were not able to collect or provide COVID-19 data. Hence, the research narrowed the timeline down to April 2020 - November 2020 because it was a period of time where the majority of countries had already been impacted by the pandemic and were able to collect COVID-19 policy and case data consistently. This removed most null values; the few countries missing most data across the research time period were further removed. The remaining small amount of null data was replaced by the monthly average of the country.

To address challenge #2 listed in section 2 - Missing Data for Calculating the Monthly Case Increase Rate for the last month of a country's dataset - the research took an approach of duplicating the previous month's monthly case increase rate for the last month. Thus, November 2020's Monthly Case Increase Rate was set to the October 2020's Monthly Case Increase Rate. Though this means November 2020's increase rate is not exact, it should only have limited impact on the overall data analysis because it only accounts for around 12.5% of the overall data, and the previous month's data should be relatively close to the current month.

The final data set includes the country code, daily policy enforcement level for each of the 12 policies, daily COVID-19 case numbers, and calculated monthly case increase rate across 168 countries in eight months (April 2020 - November 2020).

Third, Google Sheets was used to create graphs for stringency index and each policy's enforcement levels against the monthly coronavirus case increase rate to show their relationships.

Fourth, Google Colab and Python were used to develop a monthly case increase rate prediction model based on the final data set created in step 2 with the calculated "monthly case increase rate" column as the target/label. The developed COVID-19 monthly case increase rate predictive machine learning model (linear regression) is $y = -15.816x_0 + 10.607x_1 - 6.335x_2 + 5.184x_3 - 1.853x_4 - 20.557x_5 - 19.102x_6 + 3.194x_7 + 16.658x_8 - 25.029x_9 - 144.590x_{10} - 14.722x_{11} + 483.090$, with x_0-x_{11} (independent variables) being the enforcement levels of each of the 12 policies(facial covering, stay at home requirements, gathering restrictions, close public transportation, cancel public events, testing policy, international travel controls, internal movement restrictions, contact tracing, school closures, public information campaigns, workplace closures) respectively, and y being the predicted monthly case increase rate(dependent variable). The model's R-squared value is around 0.188.

Finally, the graphs (from step 3) and models (from step 4) were analyzed to draw conclusions by integrating them into an effectiveness index. The formula to calculate the index would look at each policy's graph and whether the case rate decreased when the enforcement level went from zero (no enforcement) to one, whether the case rate continued to decrease every time the enforcement level increased, and then look at the machine learning model and check whether the coefficient of the policy was negative or not. The policies that met all three categories would be classified as the most effective and consistent policies; the policies that met two out of three categories would be classified as partly effective and consistent policies; and the policies that met one out of three categories would be classified as not effective and consistent policies. A more detailed illustration of the approach addressing challenge #3 is described in section 4.3.

4. EXPERIMENTS/EVALUATION

4.1. Monthly Case Increase Rate vs. Policy Enforcement Level Graphs

4.1.1. Experiment Setup

After cleaning the data, Google Sheets was used to create graphs for the stringency index and each policy's enforcement levels against the monthly coronavirus case increase rate to show their relationships, as shown in Figure 2 and 3 below.

4.1.2. Experiment Results

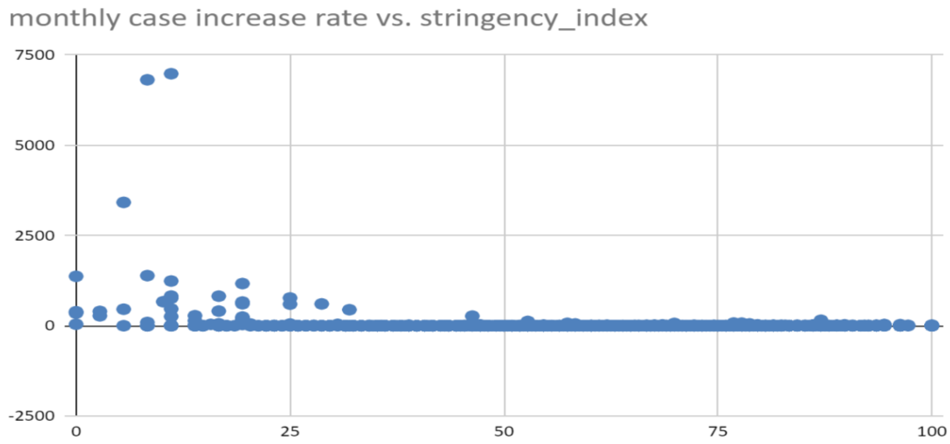
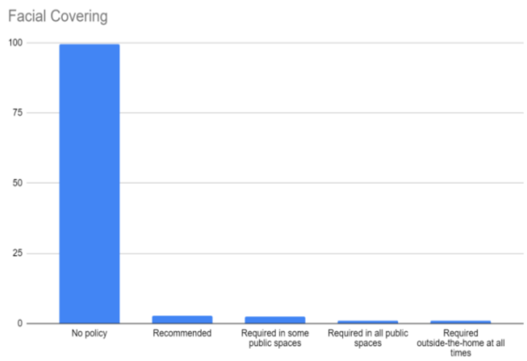
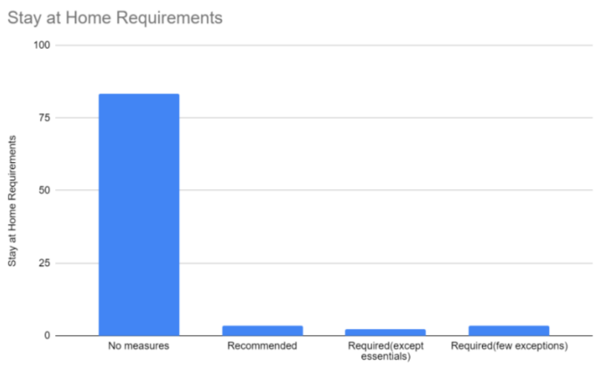
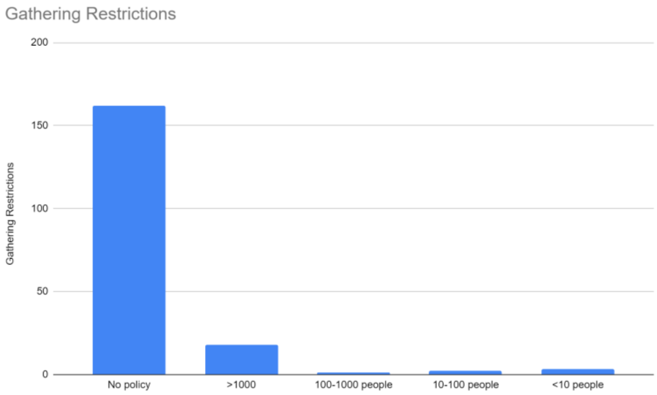


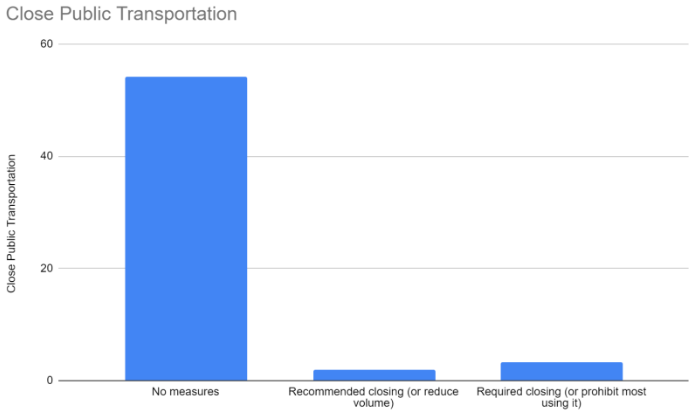
Figure 2. Monthly Case Increase Rate (y-axis) vs. Stringency Index (x-axis) Graph

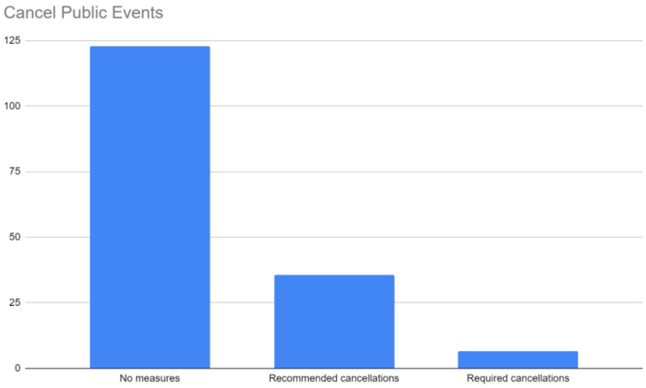
As Figure 2 shows, when plotting the monthly case increase rate against the stringency index (which has a value between 0 to 100 with 100 being the strictest response), it was very noticeable that for the stringency indexes between 0-25, meaning the country was very loose on policies and enforcement, monthly case increase rates were the highest. From then on until 100, as the stringency index gradually became stricter, monthly case increase rates became very minimal. The highest monthly case increase rate was 6981% at a stringency index of 11.11, while the lowest monthly case increase rate was around 3.726% at a stringency index of 100.

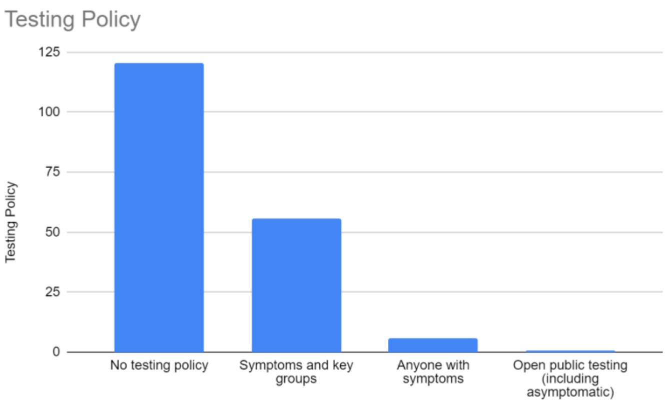


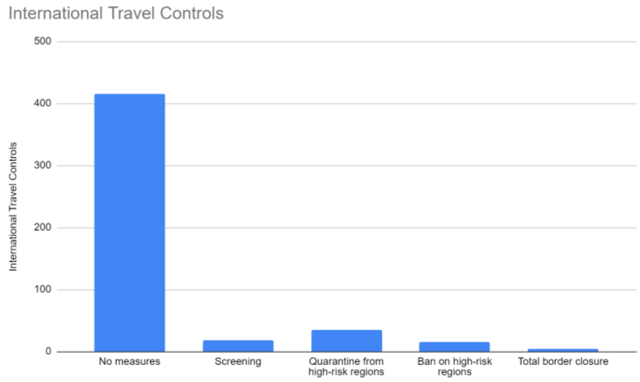


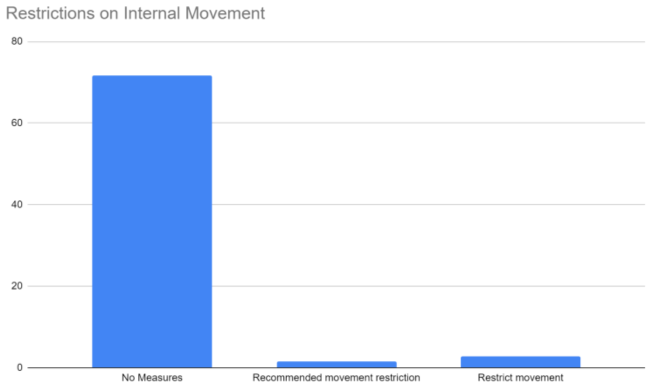

Gathering Restrictions
200
150
100
50
0
Gathering Restrictions
No policy
>1000
100-1000 people
10-100 people
<10 people

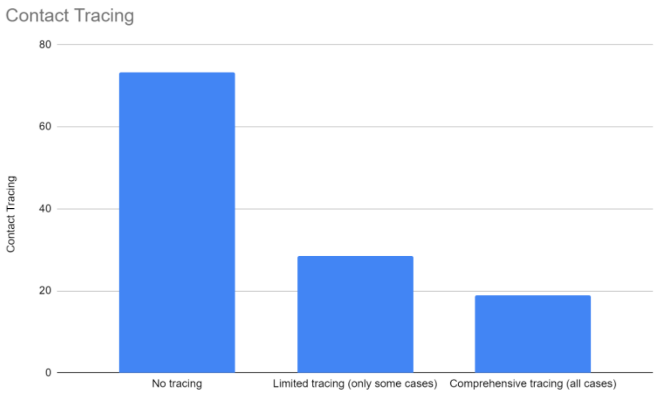

Close Public Transportation
60
40
20
0
Close Public Transportation
No measures
Recommended closing (or reduce volume)
Required closing (or prohibit most using it)

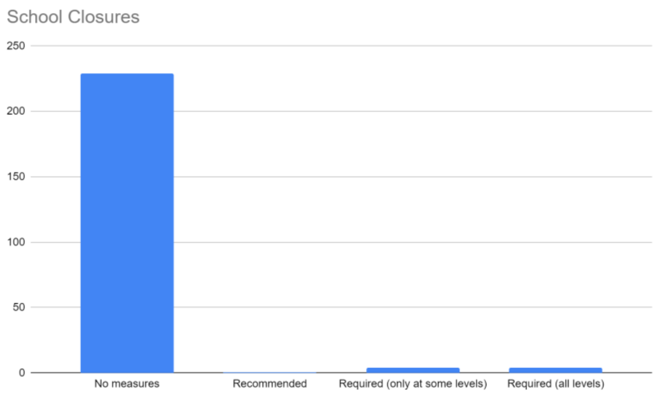

Cancel Public Events
125
100
75
50
25
0
No measures
Recommended cancellations
Required cancellations

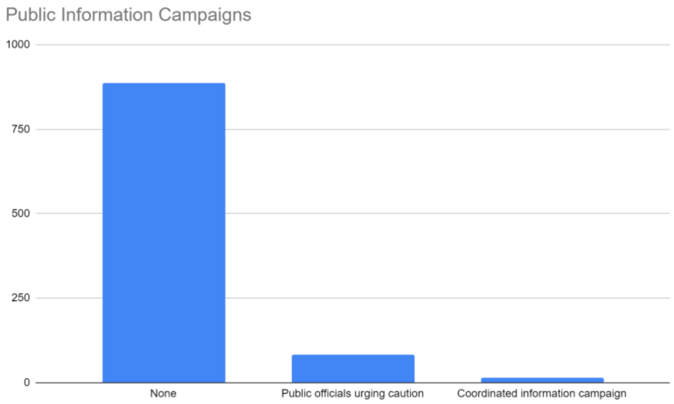

Testing Policy
125
100
75
50
25
0
Testing Policy
No testing policy
Symptoms and key groups
Anyone with symptoms
Open public testing (including asymptomatic)


International Travel Controls
500
400
300
200
100
0
International Travel Controls
No measures
Screening
Quarantine from high-risk regions
Ban on high-risk regions
Total border closure


Restrictions on Internal Movement
80
60
40
20
0
No Measures
Recommended movement restriction
Restrict movement


Contact Tracing
80
60
40
20
0
Contact Tracing
No tracing
Limited tracing (only some cases)
Comprehensive tracing (all cases)


School Closures
250
200
150
100
50
0
No measures
Recommended
Required (only at some levels)
Required (all levels)



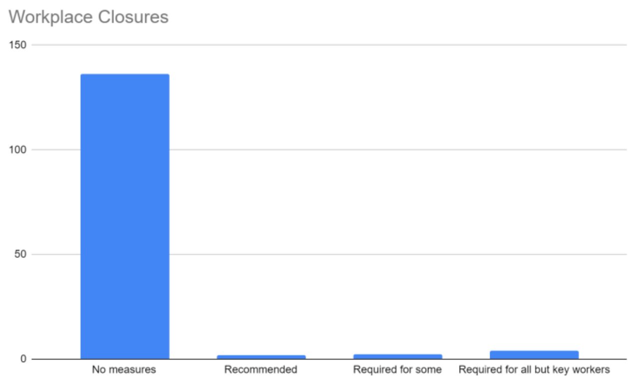


Figure 3. Monthly Case Increase Rate(y-axis) vs. Policy Enforcement Level(x-axis) Bar Graphs for all 12 common COVID-19 policies

As all of the above policy bar graphs (in Figure 3) show, there is a consistent sharp drop in monthly case increase rates from no policy to the first level of strictness across all policies. Without any kind of policy in play, citizens were able to go on about their daily lives without taking any precautions for the rapidly spreading virus. The result of that was mass virus spread and a quick increase of case and death numbers. However, as soon as the first level of strictness was put into play, though it was usually just a simple recommendation, it drastically lowered monthly case increase rates because people understood more about the threat the coronavirus posed and took action to protect themselves.

Based on the bar graph results and analysis, the ideal strictness levels for each policy to maintain the lowest monthly case increase rate are: Facial Covering - Required outside the home at all times; Stay at Home Requirements - Required(except essentials); Gathering Restrictions - 100-1000 people; Close Public Transportation - Recommended closing(or reduce volume); Cancel Public Events - Required cancellations; Testing Policy - Open public testing(including asymptomatic); International Travel Controls - Total Border Closure; Restrictions on Internal Movement - Recommended Movement Restriction; Contact Tracing - Comprehensive Tracing(all cases); School Closures - Recommended; Public Information Campaigns - Coordinated Information Campaign; Workplace Closures - Recommended.

A noticeable aspect that appeared in half of the bar graphs though, was that the strictest level of implementation did not always mean the lowest monthly case increase rate. This was the case for the policies: stay at home requirements, gathering restrictions, closing public transportation, restrictions on internal movement, school closures, and workplace closures. There are a couple of possible reasons that could cause this: 1) These policies may be harder to implement; 2) These policies may take a longer time to have an impact on the monthly case increase rate; 3) These policies may be not fully independent and partially depend on other policies' effectiveness.

To validate reason 3), six tables were created, each of which included one of the six policies that did not have the strictest enforcement level with the lowest monthly case increase rate. Those tables show the average monthly case increase rate against the enforcement level of each of those six policies. A column showing the average monthly case increase rate against the facial-covering enforcement level to contrast the two different policies was also included.

Policies where the strictest level did not have the lowest monthly case increase rate		
Figure 17-1		
Monthly Case Increase Rate	Stay at Home Restrictions Strictness Level	Facial Covering Average Strictness Level
2.352745818	2	2.211618257
3.549765103	3	1.653846154
Figure 17-2		
Monthly Case Increase Rate	Gathering Restrictions Strictness Level	Facial Covering Average Strictness Level
1.200736219	2	2.212903226
3.235576432	4	2.163934426
Figure 17-3		
Monthly Case Increase Rate	Close Public Transportation Strictness Level	Facial Covering Average Strictness Level
1.895178661	1	2.276643991
3.310951009	2	1.830388693
Figure 17-4		
Monthly Case Increase Rate	Internatl Movement Restrictions Strictness Level	Facial Covering Average Strictness Level
1.459544154	1	2.153508772
2.744722343	2	2.068078669
Figure 17-5		
Monthly Case Increase Rate	School Closures Strictness Level	Facial Covering Average Strictness Level
0.5801490649	1	2.344827586
4.081160776	3	1.883561644
Figure 17-6		
Monthly Case Increase Rate	Workplace Closures Strictness Level	Facial Covering Average Strictness Level
1.94598019	1	2.304878049
3.92522906	3	1.528384279

Figure 4. Policies Whose Strictest Level not Lowest Monthly Case Increase Rate vs. Facial Coverings

All the six tables consistently showed that whenever the facial-covering policy enforcement level average was higher, the monthly case increase rate was lower, despite the fact that the enforcement level of each of the six policies were lower. For example, when the stay-at-home enforcement level was at 3 the monthly case increase rate was higher than that when the stay-at-home enforcement level was at 2. This could be because when the stay-at-home enforcement level was at 3, the facial-covering enforcement average was around 1.65, which is lower than the facial-covering enforcement average at around 2.21 when the stay-at-home enforcement level was at 2. This indicates that the monthly case increase rate depends more on the mask-wearing policy enforcement level rather than those six policies like stay-at-home requirements.

Similarly, policies like school and workplace closures also depend more on the facial covering policy. Since some citizens really do need to be working and attending school outside of the house, it is okay not to implement the strictest enforcement level as long as they strictly follow the mask-wearing policy.

4.2. Machine Learning Model

4.2.1. Setup

To develop a monthly case increase rate prediction model and analyze each policy's enforcement level's impacts on the monthly case increase rate, the research utilized Google Colab, Python code, the sklearn library, and integrated policy related data to train and develop a Linear Regression machine-learning-enabled prediction model (refer to Figure 5 for code). The dataset was first split into the X dataset with predictor variables (the policy enforcement levels) and the y dataset with the prediction variable(the monthly case increase rate). Then, these two datasets were split into training and testing datasets with an 80%-20% split. The training X and y datasets were used to develop the Linear Regression machine-learning-enabled prediction model. The resulting Linear Regression model was then used for predictions on the X-test dataset, and these predictions were compared against the y-test dataset to evaluate the model's accuracy.

```
[4] from sklearn.linear_model import LinearRegression
    import numpy as np
    from sklearn import datasets, linear_model
    from sklearn.metrics import r2_score
    from sklearn.model_selection import train_test_split
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    from sklearn.metrics import accuracy_score

    data = pd.read_csv('theOne3.csv')

    X2 = data.drop(columns=['iso_code', 'continent', 'location', 'date', 'total_cases', 'monthly case increase rate', 'population', 'stringency_index'])

    y2 = data['monthly case increase rate']

    X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0.2)
    model2 = LinearRegression().fit(X2_train,y2_train)
    preds_test = model2.predict(X2_test)
    preds_train = model2.predict(X2_train)

    print(model2.coef_)
    print(model2.intercept_)

[ -15.8160429    10.60734783   -6.33452425    5.1840911    -1.85269972
  -20.5574149   -19.10204816    3.19390671   16.65823922  -25.02859067
 -144.58991401  -14.72203999]
483.08964874985185

print(r2_score(y2_test, preds_test))

0.188299681901963
```

Figure 5. Machine Learning Model Code

4.2.2. Results

As the linear regression formula is $y = A_0x_0 + A_1x_1 + A_2x_2 + A_3x_3 + A_4x_4 + A_5x_5 + A_6x_6 + A_7x_7 + A_8x_8 + A_9x_9 + A_{10}x_{10} + A_{11}x_{11} + B$ with y being the predicted monthly case increase rate, A_0-A_{11} being the coefficients, x_0-x_{11} being the independent policy enforcement level variables for the 12 policies respectively(x_0 = facial covering, x_1 = stay at home requirements, x_2 = gathering restrictions, x_3 = close public transportation, x_4 = cancel public events, x_5 = testing policy, x_6 = international travel controls, x_7 = internal(domestic) movement restrictions, x_8 = contact tracing, x_9 = school closures, x_{10} = public information campaigns, x_{11} = workplace closures), and B being the intercept, the developed monthly case number increase rate predictive formula is $y = -15.816x_0 + 10.607x_1 - 6.335x_2 + 5.184x_3 - 1.853x_4 - 20.557x_5 - 19.102x_6 + 3.194x_7 + 16.658x_8 - 25.029x_9 - 144.590x_{10} - 14.722x_{11} + 483.090$. Although most of the coefficients were negative, meaning the specific variable contributed to lowering the monthly case increase rate, the coefficients for the four policies, stay at home requirements, closing public transportation, restrictions on internal movement, and contact tracing, were positive. A positive coefficient means a higher policy enforcement level will increase the monthly case number increase rate, and this does not align with our common sense. The possible reasons are: 1) these four policies were harder to implement effectively as citizens may not follow them appropriately; 2) these four policies may take a longer time (e.g. more than a month) to contribute to lowering the monthly case increase rate; 3) the data used in the research was insufficient to show more accurate results.

The prediction model had an R-squared value of around 0.188. R-squared values measure the strength of correlation in the model between the independent variable and the dependent variable with a value between 0%-100% [5]. The model's R-squared value was low because it predicted a result related to/impacted by human behavior which constantly changes. R-squared values of a prediction related to/impacted by human behavior in research is usually less than 50%. Also, the data used to create the model may not be sufficient to create a solid and accurate machine-learning-enabled prediction model. When collecting more data for the coming months and years, the model can be improved. Furthermore, there could be other important independent factors (other than the 12 policies listed in ourworldindata.org) that also have meaningful impacts on the monthly case increase rate, but they were not included in the current prediction model.

4.3. Analysis

To address challenge #3 listed in section 2, the research defined an integrated policy effectiveness grade integrating the analysis results on a policy from both relationship bar graphs and machine learning enabled prediction model. As Figure 6 below shows, based on the prediction model coefficients for each policy's enforcement level and the enforcement level impact consistency shown in the bar graphs Figure 3, a policy's integrated grade can be calculated as one of 100%, 50-75%, or 25%. Policies were first given 25% if their graphs had a drop from enforcement level 0 to 1. Then, they were given 25% if they had a consistent graph, and 50% if they had a negative coefficient. All policies that were "Most Effective and Consistent" had a grade of 100%. The "Partly Effective and Consistent" policies that were School Closures, Workplace Closures, and Gathering Restrictions, received a grade of 75%; the "Partly Effective and Consistent" policy Contact Tracing received a grade of 50%. All the "Not Very Effective and Consistent Policies" received a grade of 25%.

Policy Name	Prediction Model Coefficient	Enforcement Level Impact Consistency (1 if consistent, 0 if not)	Most Effective Enforcement Level	Effectivness and Consistency Grade
Public Information Campaigns	-144.589914	1	Coordinated Information Campaign	
Testing Policy	-20.5574149	1	Open public testing(including asymptomatic)	
International Travel Controls	-19.10204816	1	Total Border Closure	100%
Facial Covering	-15.8160429	1	Required outside the home at all times	
Cancel Public Events	-1.85269972	1	Required cancellations	
School Closures	-25.02859067	0	Recommended	75%
Workplace Closures	-14.72203999	0	Recommended	75%
Gathering Restrictions	-6.33452425	0	100-1000 people	75%
Contact Tracing	16.65823922	1	Comprehensive Tracing(all cases)	50%
Restrictions on Internal Movement	3.19390671	0	Recommended Movement Restriction	
Closing Public Transportation	5.1840911	0	Recommended closing(or reduce volume)	25%
Stay at Home Requirements	10.60734783	0	Required(except essentials)	

Note:

First Tier Policies(most effective and consistent policies)	coefficient is negative and policy bar graph is consistent to show the relationship between the policy enforcement level and the monthly COVID-19 case increase rate (100%)
Second Tier Policies(partly effective and consistent policies)	coefficient is negative and policy bar graph is not consistent OR coefficient is positive and policy bar graph is consistent (50%-75%)
Third Tier Policies(not very effective and consistent policies)	coefficient is positive and policy bar graph is not consistent (25% - the inconsistent policy bar graphs still are consistent when the enforcment level increases from 0 to 1)

Effectiveness and Consistency Grade = Coefficient_Weight * Coefficient_Negative_Flag + Enforcement_Level_0_to_1_Consistent_Weight * Enforcement_Level_0_to_1_Consistent_Value + Enforcement_Level_1_Above_Consistent_Weight * Enforcement_Level_1_Above_Consistent_Value

Coefficient_Weight = 0.5	Coefficient_Negative_Flag = 1 if it is negative, otherwise = 0
Enforcement_Level_0_to_1_Consistent_Weight = 0.25	Enforcement_Level_0_to_1_Consistent_Value = 1 if it is negative, otherwise = 0
Enforcement_Level_1_Above_Consistent_Weight = 0.25	Enforcement_Level_1_Above_Consistent_Value = 1 if it is negative, otherwise = 0

Figure 6. Policy Tiers Definition and Calculations

As a result, three effectiveness and consistency groups of policies were identified - 1) Most Effective and Consistent Policies with their most effective enforcement levels (Public Information Campaigns/Coordinated Information Campaign, Testing Policy/Open public testing (including asymptomatic), International Travel Controls/Total Border Closures, Facial Coverings/Required outside the home at all time, Cancel Public Events/Required cancellations); 2) Partly Effective and Consistent Policies with their most effective enforcement levels (School Closures/Recommended, Workplace Closures/Recommended, Gathering Restrictions/100-1000 people, Contact Tracing/Comprehensive tracing (all cases)); 3) Not Very Effective and Consistent Policies with their most effective enforcement levels (Restrictions on Internal Movement/Recommended Movement Restriction, Closing Public Transportation/Recommended losing (or reduce volume), Stay at Home Requirements/Required (except essentials)).

Based on the above analysis, my hypothesis, "If a country has a higher stringency index and enforces the highest level of strictness for each policy, then the coronavirus case increase rate will decrease", is mostly (75%) correct. The stringency index against the monthly case increase rates graph seemed to decrease exponentially as the stringency index strictness increased. This meant that if a country had a higher stringency index, the coronavirus case increase rate would decrease. The analysis of the monthly case increase rate against each policy's enforcement level showed that in six out of twelve policies, the higher level of strictness contributed to a lower monthly case increase rate consistently across all levels. However, in the other six policies, the highest level of strictness did not have the lowest monthly case increase rate, although monthly case increase rates still significantly decreased from no policy to the first enforcement level.

The possible reasons for some policies not having the highest level of strictness associated with the lowest monthly case increase rate are: 1) These policies may be harder to implement appropriately; 2) These policies may take a longer time (e.g. longer than a month) to have an impact on the monthly case increase rate; 3) These policies may be not fully independent and partially depend on other policies' effectiveness; 4) The data used in my research was insufficient to show more accurate results. Future research should be conducted in these areas with more data to identify more accurate relationships between monthly case increase rates and implemented policies.

The monthly case increase rate prediction model developed based on the data from ourworldindata.org has positive coefficients for four policies - stay at home requirements, closing public transportation, restrictions on internal movement, and contact tracing. It does not make sense because it seems to mean that implementing those policies will increase the coronavirus monthly case increase rate. The possible reasons are: 1) these four policies were harder to implement effectively as citizens may not follow them appropriately; 2) these four policies take a longer time to contribute to lowering the monthly case increase rate; 3) the data used in my research was insufficient to show more accurate results. Future research should be conducted in these areas with more data.

In addition, the R-Squared value - around 0.188 - of the prediction model implied that there could be other important independent factors (other than the 12 policies listed in ourworldindata.org) that also have a meaningful impact on the monthly case increase rate, but are not included in the current prediction model yet (e.g. whether a country's leader believes in a scientific approach to handle COVID-19, how well a country follows their government's policy). When leaders (in a country or a state) publicly voiced that they did not believe or were not willing to follow a scientific approach, the case numbers seemed to increase much faster even though the overall policy enforcement level in that area was strict in the data. Because there is a lack of information about whether countries' leaders believe in a scientific approach to handle COVID-19, this factor is currently not able to be included in the model. However, this is an important area to research more in, and an interesting factor to be taken into consideration for future research.

5. RELATED WORK

The work done by Wibbens, P. D. et al [3] utilized Bayesian analysis on big data to evaluate the effectiveness of 11 widely implemented core COVID-19 policies in the U.S. It concluded that though these core policies reduced growth rates for new infections, they were still not enough to contain the virus. In order to bring the COVID-19 infection growth rate to near zero, higher-impact policies, like full workplace closures, would need to be implemented. The Bayesian approach may be useful because it updates the experiment results as more information comes in. COVID-19 is an ongoing pandemic, making Bayesian helpful in accounting for changes as time goes on. However, their work only focused on the U.S. and did not take into consideration various policy enforcement levels' (three to four levels) impact on a policy's effectiveness. The data collected in my research includes policy enforcement level and COVID-19 case numbers from 168 countries around the world. Hence, my research work's analysis is more inclusive since it includes data from many countries across the world, and is closer to countries' practice in the real world because it analyzes the policy effectiveness across different policy implementation levels.

The COVID-19 Projections model from the Institute for Health Metrics and Evaluation (IHME) [6, 7] provides graphs of projections on total deaths, daily deaths, infections and testing, hospital resource use, mask use, and social distancing in almost all countries. For total deaths and daily deaths, it includes different predictions for different circumstances, such as a circumstance if there was universal mask-wearing, a circumstance if there was a rapid vaccine rollout, and a circumstance if mandates began easing. It also compared observed data with the predicted results. The model, being a hybrid model that fuses elements of statistical analysis and disease transmission model, was created to help policymakers understand how different policy decisions can affect the trajectory of COVID-19. Based on the model they developed for the United States, they found that universal mask-wearing could be sufficient to avoid the worst effects of epidemic resurges. Another finding was that COVID-19-related mandates easing in states could lead to a cumulative total of around 511,373 deaths by February 28, 2021 because relaxed mandates would cause more open interaction and higher rates of spread. This projection model produced accurate forecasts with the lowest median absolute percentage error being 20.2% compared to 32.6% in many other models. Similar to my research, the IHME accounts for many different countries and their individual pandemic-handling situations. However, the IHME model focuses more on COVID-19 case predictions rather than also the effectiveness of COVID-19 policies. My research focuses on both aspects as they are correlated to each other. The only mentions of COVID-19 policies in the IHME predictions are "Vaccine Coverage", "Mask Use", and "Social Distancing"; but even so, there is no further detail about enforcement levels or whether they are really effective in lowering COVID-19 case rates. My research also analyzed the effectiveness impact of various enforcement levels (3 or 4 levels) of each of the 12 common COVID-19 policies on the monthly case increase rate and categorized them into three effectiveness grade levels.

The work done by Arshed, N. et al [4] utilized the Panel Random Coefficient Model to estimate the COVID-19 flattening curve and estimate the number of days it will take to reach the flattening point. It also evaluated the effectiveness of different COVID-19 policies around the world using Poisson regression, concluding that contact tracing, stay at home restrictions, and international movement restrictions are most effective in controlling spread and flattening the COVID-19 curve. However, my research took a different approach. It evaluated the effectiveness of COVID-19 policies through a quantitative analysis approach integrating a policy's coefficient in a Linear Regression machine-learning-enabled monthly case increase rate prediction model, and a policy's implementation enforcement level's impact on monthly case increase rates through bar graphs.

6. CONCLUSION

6.1. Summary

My research proved that my hypothesis is 75% correct. It concluded that: 1) If a country has a higher stringency index, then the monthly coronavirus case increase rate will decrease; 2) For all of the 12 policies from ourworldindata.org(excluding vaccination), the COVID-19 monthly case increase rate will decrease sharply (on average 89.81%) when the policies enforcement level is increased from no measure to the first/initial level of strictness; 3) If a country enforces a higher level of strictness for the six consistent and effective policies out of the 12 (facial covering, cancel public events, testing policy, international travel controls, public information campaigns, contact tracing), then the monthly coronavirus case increase rate will decrease accordingly; 4) For the other six policies (stay at home requirements, gathering restrictions, closing public transportation, restrictions on internal movement, school closures, and workplace closures), their most effective enforcement level is not the strictest.

The developed COVID-19 monthly case increase rate predictive machine learning model(linear regression) is $y = -15.816x_0 + 10.607x_1 - 6.335x_2 + 5.184x_3 - 1.853x_4 - 20.557x_5 - 19.102x_6 + 3.194x_7 + 16.658x_8 - 25.029x_9 - 144.590x_{10} - 14.722x_{11} + 483.090$, with x_0-x_{11}(independent variables) being the enforcement levels of each of the 12 policies(facial covering, stay at home requirements, gathering restrictions, close public transportation, cancel public events, testing policy, international travel controls, internal movement restrictions, contact tracing, school closures, public information campaigns, workplace closures) respectively, and y being the predicted monthly case increase rate(dependent variable). The model's R-squared value is around 0.188.

My research showed that the most common 12 policies provided by ourworldindata.org could be categorized into three levels of effectiveness and consistency with a grade of 100%, 50-75%, and 25% respectively. The First Tier Policies (Most effective and consistent) consist of Public Information Campaigns, Testing Policy, International Travel Controls, Facial Covering, and Cancel Public Events. The Second Tier Policies (Partly effective and Consistent) consist of School Closures, Workplace Closures, Gathering Restrictions, and Contact Tracing. The Third Tier Policies (Not very effective and consistent) consist of Restrictions on Internal Movement, Closing Public Transportation, and Stay at Home Requirements.

Utilizing the policy effectiveness and consistency groups, and the prediction model developed in this research, countries and public health management organizations can identify and implement the most effective and consistent policies at appropriate enforcement levels to lower monthly COVID-19 case increase rates more effectively.

6.2. Current Limitations

There currently are two main limitations of the research: 1) The linear regression prediction model's R-Squared value is only around 0.188 which is relatively low. It may be due to the limited data (11 months data) available at the time this research started; 2) It is also a question as to why some policies (e.g. stay at home restrictions) enforcement levels are higher but the monthly case increase rate does not decrease accordingly. One possible reason is that the policies may take a longer time to have an impact, or the policies may be harder to implement appropriately. Another reason, according to my initial research and analysis, is that the policies may be not fully independent and partially depend on other policies' strictness level. The research identified that the strictest enforcement levels of the six inconsistent policies do not have the lowest monthly case increase rate. However, the related strictest average facial covering enforcement level does. The average facial covering strictness level (e.g., 2.212) was calculated by averaging the strictness levels of facial covering when the associated policy (e.g. Stay at Home Restrictions) was at a specific strictness level (e.g. 2) across all the countries over all months. This meant that a lower monthly case increase rate depended more consistently on facial covering enforcement levels rather than those six inconsistent policies' enforcement levels respectively.

7. FUTURE WORK

To develop a better machine learning enabled monthly case increase rate prediction model with a higher R-Squared value, future research may include collecting more data when COVID-19 enters its second or third years, identify other potential predictors, try some other machine learning algorithms, or develop a program to automatically run multiple times to find a best model with the highest R-Squared value. Another interesting area to explore in future research is to analyze and discover the most cost-efficient and effective policies in reducing COVID-19 monthly case rates through considering policy costs and integrating it with policies' effectiveness analysis.

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