Exploring the Dynamic Relationship between COVID-19 and Pre-existing Epidemics: An Empirical and Forecasting Approach

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ABSTRACT

After the recent unfolding of the COVID-19 pandemic and the impact on the world's population and healthcare systems, there is a need to understand how COVID-19 may have affected the frequency, pervasiveness, and severity of other infectious diseases. Our study will aim to investigate the joint-dynamic relationship between COVID-19 and other infectious diseases using empirical and forecasting models. We will create and validate a forecasting model that can estimate the missing Influenza cases from the beginning of the pandemic to recent, while accounting for confounding factors such as public health policies that were enacted during the pandemic. Empirical models will be used to explain and interpret the decrease and absence in Influenza cases during the pandemic. To complete this goal we leverage large-scale, publicly available data sources, and surveillance systems to capture the relationships.

CCS CONCEPTS

• **Data Analysis**; • **Time-Series Analysis**; • **Data-Driven and Empirical modeling**;

KEYWORDS

LSTM, Time-Series Analysis, COVID-19,Data-Driven and Empirical modeling

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1 INTRODUCTION

The unprecedented emergence of the COVID-19 pandemic has had significant impacts on global public health systems and the lives of people from all around the globe. While all of the world has been battling the quick spread, new public health measures, and consequences of the coronavirus, there is still pre-existing epidemics that pose a significant threat to public health. There is a need to understand the intricate interplay between COVID-19 and the pre-existing infectious diseases in order to devise effective public health strategies and to ensure the well-being for affected populations. During the pandemic global healthcare systems and resources were strained and put to the test. This may have inadvertently affected the normal dynamics of other seasonal infectious diseases such as Influenza. The given situation highlights the importance of investigating the impact of the pandemic on pre-existing epidemics. By leveraging empirical and forecasting models, we aim to analyze the complex interactions between COVID-19 and other diseases. The models we create will aim to help public health officials and policy-makers in making informed decisions and facilitating the implementation of targeted and evidence-based interventions. To complete our objective, we will utilize accessible data sources and monitoring systems to gather and examine information. Our investigation will concentrate on assessing the efficacy of various public health policies across specific countries and regions in reducing the effects of epidemics. This research seeks to explore the complex connections between COVID-19 and other infectious diseases. By doing so, we hope to offer valuable insights that will contribute to the creation of resilient approaches for navigating and controlling global pandemics.

2 PROBLEM DEFINITION

The primary objective of this study was to analyze the impact of the COVID-19 pandemic on Influenza trends and cases across different countries. The study initiates by considering a cumulative global model, subsequently delving into specific countries, namely the US, Sweden, and China. The COVID-19 pandemic catalyzed significant changes in public health, policy-making, and social behavior, which inadvertently affected the typical circulation and spread of Influenza. To effectively strategize for future disease outbreak management and to deepen our understanding of the pandemic's indirect consequences, it is crucial to study the influence of COVID-19 on seasonal Influenza trends. We break down this problem into the following components:

(1) Explore the alterations in Influenza trends before and during the COVID-19 pandemic, highlighting the decline in cases from early 2020 to the end of 2021, and the subsequent resurgence of the normal Influenza trend.
(2) Evaluate the influence of public health policies and interventions, such as mask mandates, social distancing measures, and limitations on gatherings, on the circulation of Influenza viruses in the selected countries.
(3) Train the model: The model is trained using a specified number of epochs and batch size on the collected dataset, which includes features relevant to the study.
(4) Develop an LSTM model to estimate the number of Influenza cases that would have occurred without the COVID-19 pandemic (2020-2022) in the United States, China, and Sweden, factoring in other relevant variables.

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(5) Using the differences in our estimated models and real-world data, analyze the policies and factors to find trends revealing what had the most impact on reported cases.

By addressing these components, the study aims to offer a comprehensive and insightful understanding of the interplay between COVID-19 and Influenza. The findings will aim to assist public health authorities in formulating data-driven policies and strategies to manage infectious diseases amidst the ongoing pandemic and potential future outbreaks.

3 RELATED WORK

Our research examined various sources to gain valuable insights into the impact of COVID-19 on non-respiratory and respiratory diseases. The Japanese observational study [Komori] [6] investigated the pandemic's effect on non-respiratory diseases such as enterocolitis and sexually transmitted diseases. The study presented a clear and concise overview of the reduction in non-respiratory infections, making it a valuable resource for constructing data-driven models. Another study from Germany [Heinzinger21] [4] analyzed oropharyngeal swabs for Influenza viruses over two consecutive Influenza seasons. The research identified a shift from Influenza to COVID-19 between the two seasons, providing instrumental data for anticipating Influenza seasonal trends and specific time frames to investigate. The Canadian study [Groves21] [2] covered respiratory viruses, including Influenza, RSV, PIV, and others, in the five seasons preceding 2022. This comprehensive research corroborated the declining trend of Influenza cases since the onset of the COVID-19 pandemic, offering extensive data from the pre-pandemic era for constructing our own models. We also reviewed a survey-based study [Wright22] [7] that investigated the impact of COVID-19 on the CDC's prevention programs for sexually transmitted infections. The study reported a general decrease in positive STD cases, including chlamydia, gonorrhea, and syphilis. Although brief and lacking specific empirical data, the participation of 59 different prevention units reporting similar findings adds validity to the study's conclusions. The New Zealand study [Huang21] [5] provided a comprehensive description of the non-pharmaceutical measures enforced in the country to reduce Influenza-like infections. Despite its limitations in identifying the most significant contributing interventions due to numerous measures implemented by public health authorities, the study still offers valuable insights into the reduction of Influenza cases. The Chinese study [Guo] [3] aimed to illuminate the effect of COVID-19 on Influenza in Southern and Northern China over two consecutive Influenza seasons. This research allowed for a detailed stage-by-stage breakdown of China's zero COVID policy. However, a potential limitation is the underestimation of the Influenza epidemic's incidence due to decreased visits to clinics and hospitals during the pandemic. Lastly, a study [Feng21] [1] investigated the effects of COVID-19 outbreaks and interventions in both China and the United States. The research methodology employed time-series models to match the historical Influenza activity during the 2019-2020 Influenza season. The researchers developed a hypothetical scenario in which COVID-19 had not emerged, and no non-pharmaceutical interventions were introduced. This approach facilitated a comparative examination of the outcomes across both nations while taking into account various health measures. In summary, the investigations carried out in these diverse studies concerning the effects of COVID-19 on prior epidemics have offered valuable knowledge to inform our research project. Together, these studies present crucial data-driven models that can aid us in developing empirical and forecasting models to anticipate future patterns in Influenza and other pre-existing infections amid pandemics.

4 PROPOSED METHOD

In this section we will present our proposed method for analyzing the impact of the COVID-19 pandemic on the prevalence of Influenza cases and interplay on seasonal Influenza trends. We start with empirical models that were created to identify patterns in the historical data of Influenza cases. These models help establish a baseline understanding of the interplay between the pandemic and Influenza trends. Our method will also rely on a Long-Short-Term (LSTM) model to forecast based on prior Influenza trends to show what Influenza cases should have looked like over the pandemic period.

4.1 Intuition

Our proposed method will aim to offer improvements over the state-of-art models by addressing the following points:

(1) Empirical Model Insights: The incorporation of empirical models allows us to identify significant patterns and correlation in historical data. Some of the models include a cumulative model of Influenza cases, the subset model of Influenza cases, sample collection, and cumulative policy decisions. The Influenza models provide the foundation for the LSTM model forecasts. These empirical models can not only improve the understanding of the relationship between COVID-19 and Influenza trends but also serve as a benchmark for addressing the performance of the LSTM model. By integrating empirical models into our approach, we are ensuring that our method is grounded in a thorough analysis of the available data, offering a more robust comprehensive perspective on the problem.

(2) Robust Model: LSTM models are designed to handle time-series data and is able to capture a long-term dependency, making them suitable for the forecasting problem. They have been shown to be more effective at time-series forecasting than traditional methods, such as Auto-regressive Integrated Moving Average (ARIMA) models.

(3) Policy Integration: By incorporating policy decisions related to COVID-19, our method will allow for a better understanding of the direct impact of these policies on Influenza trends. This aspect sets our approach apart from other studies, which do not always consider the impact of policy on dynamics of the two diseases.

(4) Subset Analysis: By examining specific countries as subsets we can explore regional variations and the effect of policy on a more localized scale. This granular approach provides more understanding of the complex interplay between COVID-19 and Influenza.

4.2 Description

Our approach consists of the following steps:

(1) Data Collection and Pre-processing data: We collected Influenza data from years prior to the beginning to the pandemic to the end of 2019. The data is collected from the World Health Organization (WHO). The data is cleaned, and some outliers are removed using the IQR method, then normalized and scaled. This process is necessary to help the LSTM model better learn the trends.
(2) Empirical Model Development: We construct empirical models, including a cumulative world Influenza model of Influenza and subset models for the chosen specific countries, as well as COVID-19 cases. These models will help identify correlations in the historical data and serve as foundational for the LSTM model.
(3) LSTM Model Development: We develop the LSTM model for the time-series forecasting, which are cabpable of identifying the long-term dependencies in the data. We train this model on the pre-processed data mentioned earlier. This model is evaluated with MAE and RMSE metrtics.
(4) Policy Integration: We incorporate policy decisions related to COVID-19 into the models, quantifying the number of policies enacted in each subset country. This allows us to establish a trend between the increase in policy decisions (e.g. masks, social distancing, group limitations) and the absence of Influenza cases.
(5) Forecasting and Analysis: Using the LSTM models, we generate forecasts for Influenza cases and visualize predictions alongside the actual data, along with computed confidence intervals to convey the level of confidence in the models predictions. This forecasting with aim to show what Influenza should have been like during the COVID-19 pandemic during the 2020 outbreak.
(6) Subset Analysis: We create the LSTM models for each subset country to investigate any regional variation and policies that impacted the Influenza trends. This provides a more detailed understating of the relationship between COVID-19 and Influenza in different regions.

By integrating empirical and LSTM models into our approach, we can gain a comprehensive understanding of the historical data and generate more accurate forecasts. These two models allow us to establish a strong foundation for our analysis and help us make more informed conclusions.

5 EXPERIMENTS AND RESULTS

Here we will break the experiments and results down into the two categories (empirical and forecasting) and do an in-depth analysis on the approaches and results. In this section we will attempt to answer these questions:

(1) Does the onset-of the COVID-19 pandemic and subsequent health policies have a significant impact on the number of reported Influenza cases?
(2) Can we observe a correlation between the COVID-19 cases, enacted health polices, and the number of Influenza cases?
(3) Does the LSTM model offer a relevant forecast of Influenza cases during the COVID pandemic years considering the historical data?

The primary data source used was from the World Health Organization (WHO). The time-span of collected data spans from 2000-2020 depending on the specific model that was constructed. For the empirical experiments of the paper, standard techniques were applied using Python's Pandas Library, which allowed for effective data manipulation and analysis. Graphical visualizations are created to present the observed trends. For the forecasting experiments, LSTM model was used. LSTM, a type of recurrent neural network (RNN) was implemented using the TensorFlow library.

5.1 Empirical Modeling

In this section we will review the experiments and results of constructed empirical models. We will focus heavily on the observations and interpretations of the data. The empirical models will aim to show and explain the disappearance in Influenza cases over the pandemic period (2020-2022). The data collected is from the World Health Organization (WHO) is raw numbers on Influenza A and Influenza B cases reported from specimen collection. Due to formatting and allocation of space we will show the results from one of the chosen subset countries.

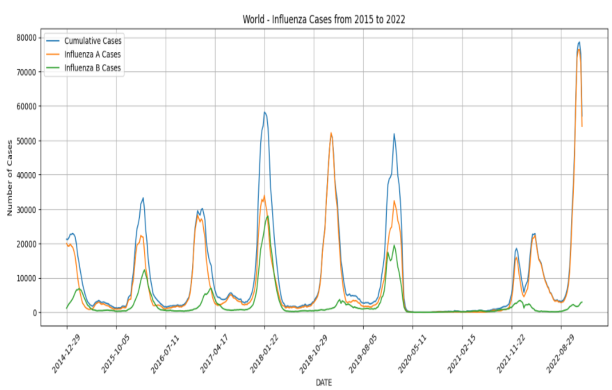

Figure 1: World wide Influenza Cases

5.1.1 Cumulative Influenza mode. Figure 1 illustrates a cumulative model of Influenza cases from 2015 to 2022, more specifically capturing the cumulative total of Influenza and Influenza B cases. From the plot, we can discern a significant drop in Influenza cases in the beginning of 2020 which coincides with the COVID-19 outbreak. The decline could be attributed to multiple factors such as stringent public health measure implementations, which had inadvertently reduced the spread of other respiratory viruses like Influenza. The resurgence of reported cases near the end of 2021 could suggest a return to pre-pandemic social behavior or waning effectiveness of measure implemented. This shows that the decline in Influenza cases was not localized to certain regions and countries but a worldwide phenomenon. We seek to explain the decline attributed to factors such as stringent public health measure implementations. This trend was also noticeable in the subset countries analyzed. To investigate this claim further we will look at an example subset we will go more granular and look at a subset example.

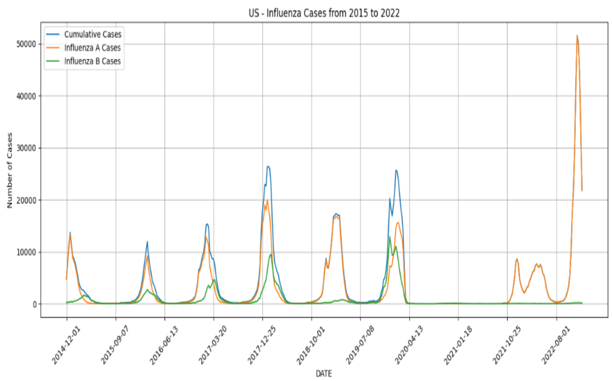

Figure 2: US Influenza Cases

5.1.2 Subset Influenza model. Figure 2, shows the trend of Influenza cases in the United States from 2015 to 2022. We can see a sharp decline beginning in early 2020, which persists until late 2021. This trend is similar to the global model observed previously. The reduction for cases in the US trends with the onset of the COVID-19 pandemic, which again implies a possible correlation between health measure and change in social behavior. So far this is in support of the initial hypothesis that external factors surrounding COVID-19 have had an impact on Influenza cases.

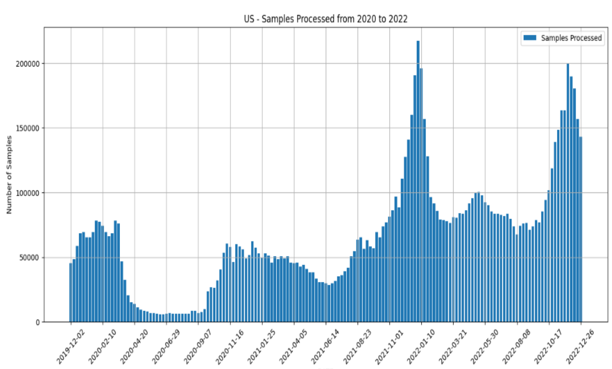

Figure 3: US Samples Processed

5.1.3 Sample Collection. Figure 3 depicts the number of processed samples over the pandemic period. This data was again collected from the World Health Organization. At about midway through 2020 the number of samples processed took a relatively big decrease. Then resumed a consistent trend near the end of 2020. With this in mind the lack of testing could explain some of the decrease in influenza cases, but near the end of 2020 returned to normal consistently. This suggest that the lack of cases is more attributed to policy interventions.

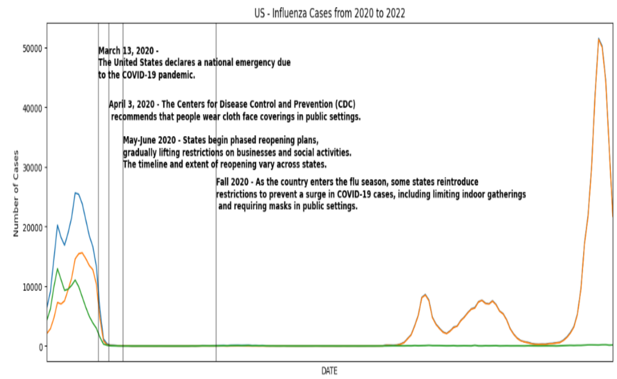

Figure 4: US Samples Processed

5.1.4 Subset Timeline. Figure 4 is a visualization of Influenza cases in the United states from 2020 to 2022 with critical events to provide context. On March 13, 2020, the United States declared a national emergency due to the COVID-19 pandemic. In the United States, the CDC recommended the use of cloth face coverings in public settings on April 3, 2020. These measures likely had an impact on the transmission of Influenza, contributing to the drastic reduction in reported cases. From May to June 2020, states started phased reopening plans, gradually lifting restrictions on businesses and social activities. Despite this, the number of Influenza cases remained low, possibly due to continued public adherence to health measures such as mask wearing and social distancing. By Fall 2020, as the country entered the flu season, some states reintroduced restrictions to prevent a surge in COVID-19 cases, including limiting indoor gatherings and requiring masks in public settings. This likely helped keep the Influenza cases low during what is traditionally the peak season for Influenza. This analysis can show how public health interventions, changes in public behavior, and policy decisions during the COVID-19 have had a significant impact on the transmission of Influenza. At the same time the introduction of policies underscores the effectiveness in controlling respiratory illness. Similar timeline plots were constructed for the other subset countries.

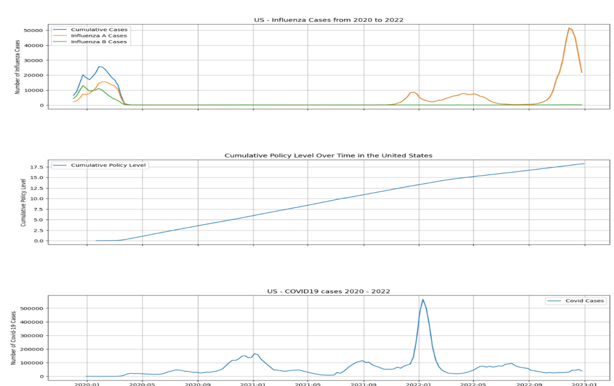

Figure 5: US Influenza, Policy, and COVID-19

5.1.5 Policy, COVID-19, and Influenza Correlation. Figure 5 illustrates three separate plots. The first plot being recorded Influenza cases over the 2020-2022 period, the second is the cumulative policy's enacted over in the United states over the same time period, and the third is the number or COVID-19 cases within the same time period. By interpreting these observations collectively, we can infer a strong correlation between the three variables. As the number of COVID-19 cases increase, more public health measures were enacted to curb the spread. These policies in turn, seem to have unintentionally mitigated the spread of Influenza. This dynamic is evident through the substantial decrease in Influenza cases, coinciding with the rise in COVID-19 cases and the policy level. This underlines the potential effectiveness of public health measures.

5.2 LSTM Modeling

In this section we will review the experiments and results conducted with the LSTM model. This analysis was completed for each of the subset country, with the additional results collected in the supplemental material. We will focus heavily on the observations and interpretations of the data. The LSTM will attempt to provide a timeline of expected Influenza cases given COVID-19 and medical policy's hadn't taken place, and what the normal trend should have looked like over the vacant years.

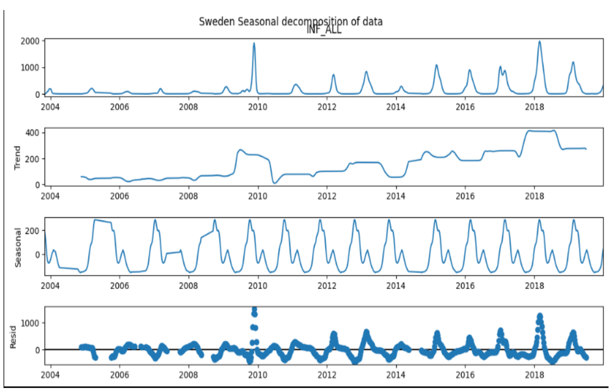

Figure 6: Model Decomposition

5.2.1 Model Trend Decomposition. Figure 6 shows data decomposition from the one of the subset countries (Sweden). To begin the first graph that is part of the plot in figure 6 shows us the raw original time series data for Influenza cases in Sweden from 2004 to 2009. The next plot shows the long term progression of the time series. As observed, the plot shows us a general increase in trend of reported Influenza cases over time. This increase could be interpreted by some different factors such as a change in susceptible population size or density or different more infectious strains. To fully understand the factors behind this trend would require further investigation. The third plot shows the seasonal cyclic pattern of Influenza cases over time, in this case annually. The plot shows the expected patterns of Influenza where cases tend to rise in the colder months (fall and winter) and decrease in the warmer months (spring and summer). This seasonal pattern could be explained due to colder months where people send more time indoors where closer contact and transmission of Influenza leads to an easier spread. Colder weather can also lead to a weakened immune system making individuals more susceptible to infections. The final plot shows the remaining information that the other two plots (trend and seasonal) did not capture. In other words we could think of this as extracted noise from the data. As we can see the model has captured a fair amount of noise that is filtered and led to a better trend and seasonal plots. Since each new flu year isn't exactly the same we would expect to see fluctuations that don't contain any discernible patterns. This suggest that our model is well-suited for forecasting.

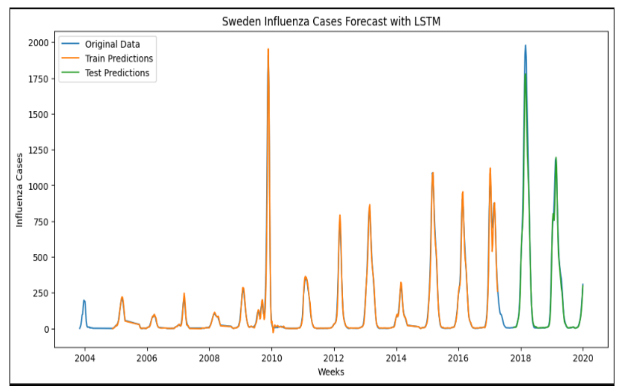

Figure 7: Model Training

5.2.2 Training the model. Figure 7 is a demonstration of training the LSTM model on the time-series data of Influenza cases. LSTM was chosen due to its ability to capture long-term dependencies to make accurate forecast. The training process is implemented as follows; the data is reshaped and normalized between 0 and 1. The data is then split into a training and testing set with an 80, 20 split respectively. Datasets have a look back period of 104 (two years of data), which means the model will use the data from the past 104 weeks to predict the following week. This value was based on the cyclic nature of Influenza cases and offered the best performance for the model. Upon plotting the data and predictions, we find that our LSTM model fits the training data well, which indicates that the model learned the patterns effectively. The models predictions on the testing data follows the closely, this demonstrates the models ability to generalize learning to new data. This is a promising result as it shows the LSTM model is able capable of accurately forecasting Influenza cases based on the past data.

5.2.3 Model Evaluation. Figure 8 presents the evaluation metrics for the LSTM model on both the training and testing datasets for Influenza cases in Sweden. The two metrics in the figure show, the Mean Absoulute Error, and Root Mean Square.

The Mean Absolute Error (MAE) measures the average magnitude of the errors in a set of predictions. It can be expressed mathematically as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

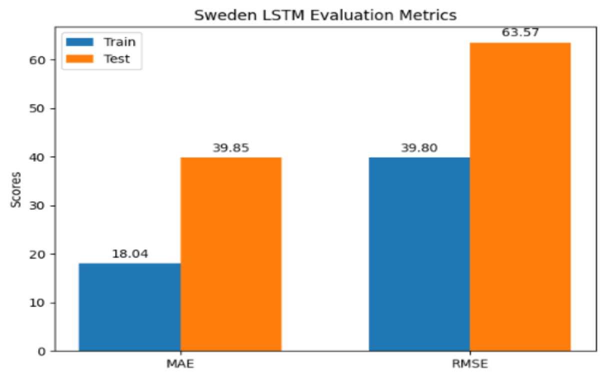

Figure 8: Model Evaluation

where y_i is the actual value, $\hat{y_i}$ is the predicted value, and n is the total number of observations. For this specific subset, the MAE value was 18.04 for the training data and 39.85 for the testing data. This indicates that on average, our model's predictions deviate by about 18.04 cases from the actual number of cases for the training set and about 39.65 cases for the testing set.

The Root Mean Square (RMSE) is a another measurement of error. It can be represented mathematically as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

where again, y_i represents the actual value, $\hat{y_i}$ is the predicted value, and n is the total number of observations. For this subset the RMSE value was 39.80 for the training data and 63.57 for the testing data. This indicates on average, the model's predictions deviate by about 39.80 for the training set and 63.57 for the testing set.

By comparing these two metrics there is a noticeable error between the training and testing data, which could suggest some over-fitting. Some regularization and early stopping was experimented with but had ultimately skewed the forecasting results. It is also worth noting that while the model produce a degree of error, it can still be useful, given the difficulty of forecasting health trends such as Influenza.

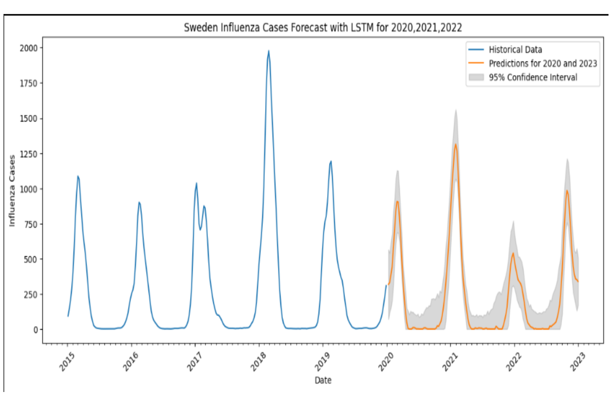

Figure 9: Model Forecast

5.2.4 Model Forecasting. Figure 9 shows the performed foretasted predictions of Influenza cases in Sweden for the years 2020,2021, and 2022 using the LSTM model previously trained on the historical data from 2004 to 2019. This experiment aims to account for the missing cases from 2020-2022 due to the COVID-19 pandemic and the health policies enacted. The experiment runs multiple simulations for each prediction to estimate the confidence interval around the initial prediction. The final forecast visualized shows the historical data, the predicted values, and the 95% confidence interval. The confidence intervals were calculated as follows:

$$LowerBound = \mu - 1.96 * \sigma$$
$$UpperBound = \mu + 1.96 * \sigma$$

where μ represents the mean and σ is the standard deviation. The plot was able to make a reasonable prediction of what we would have expected Influenza cases to look like over the 2020-2022 period. The seasonal pattern earlier is found again where there would be a rise of cases in the colder months with a decrease in the warmer months. This aligns with the known behavior of Influenza transmission. It is worth noting that the predictions are under the assumption that future Influenza trends will follow the same patterns as observed in the historic data. They do not take into account potential future variations of future Influenza strains, changes in vaccination rate, or other public health intervention. For this reason, the results of this experiment should be looked at within the context of the limitations and uncertainties.

6 OLS REGRESSION ANALYSIS

Taking the forecasts we were are able to create data sets for each country that included all of our available data previously processed into our bulk set. We achieved this by getting a select countries forecast, then merging with the bulk set, providing all possible data we can have for one country at a time. Importing our set we assigned the Dependent Variable as the difference between our forecast and reported amounts of Influenza cases. Independent variables consisted of all other data points that we were able to offer, while building two sets to ensure consistency with including COVID-19 case data and excluding it. We ran the data sets through OLS, Ordinary Least Squares, modeling we found promising results. In comparison of the sets we found that while the COVID-19 including set has lower standard error, the sets performed with similar trends overall. Because of this we will stick with the COVID-19 inclusive sets within our figures and conclusions. WLS, Weighted Least Squares, modeling is an option for similar data sets, but without a weighting scheme for independent variables will return and was returning the same results as OLS. Figure 10 shows results from the analysis of Sweden's independent policies. With these results we infer that a more positive "coef" or coefficient score indicates that policy having higher impact on reducing Influenza cases below the forecast levels. We look at positive coefficients due to us comparing the increasing difference in forecast and reported cases with increasingly policy strictness. We want a positive correlation here where both are increasing. The common trend in both our Sweden and China results shows that public information campaigns were the most important factor. The US results show the same when accounting for the policies very large standard error. From

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	27.0115	15.493	1.743	0.082	−3.389	57.412
facial_coverings	−1.5925	6.410	−0.248	0.804	−14.171	10.986
contact_tracing	−23.9395	5.925	−4.041	0.000	−35.565	−12.314
vaccination_policy	−10.5810	3.496	−3.026	0.003	−17.442	−3.721
public_information_campaigns	38.1523	12.332	3.094	0.002	13.955	62.350
school_closures	16.2837	5.369	3.033	0.002	5.750	26.818
workplace_closures	76.5674	9.943	7.701	0.000	57.057	96.078
stay_home_requirements	5.8634	14.165	0.414	0.679	−21.932	33.658
cancel_public_events	−91.9610	14.908	−6.169	0.000	−121.214	−62.709
restriction_gatherings	16.2584	4.579	3.551	0.000	7.274	25.243
close_public_transport	−33.5744	11.841	−2.835	0.005	−56.809	−10.340
restrictions_internal_movements	−61.6901	8.936	−6.904	0.000	−79.223	−44.157
international_travel_controls	−8.6006	4.555	−1.888	0.059	−17.538	0.337
DAILY_CASES_Covid	−0.0011	0.001	−1.656	0.098	−0.002	0.000
DAILY_CASES_DEATHS_Covid	1.4748	0.132	11.205	0.000	1.217	1.733
PERSONS_TESTED_Covid	0.0003	0.000	1.331	0.183	−0.000	0.001

Figure 10: Sweden OLS Model Results

this we understand that public awareness of health and proper precautions played a vital role in reduction of Influenza spread. This rings true, a more aware public is more likely to follow sanitation practices, take mild illness more seriously, and avoid risky behaviors. Other leading policies were a mix of different reductions in public interactions. Cancellation of public gatherings, restrictions on internal movements, and closures all lowered real-world case numbers. This intuitively makes sense as these variables all involve interaction of the public, where reducing these pathways reduces the opportunities for spread. This trend of reducing public interactions remains across analysis of all countries, but no distinct individual policy outliers emerge. This is not unexpected, countries differ from each other, and the minute details of daily life will vary significantly. While other policies certainly had impact on both Influenza and COVID-19 spread alike, they were less influential in our model results. Policies such as "vaccination" for COVID-19 were not expected to have impact on Influenza cases, but there may be residual benefit from the general health advertisement to the public. For other policies returning negative correlations that should have intuitive benefits, we suspect suffered from differences in their introductions on COVID-19's trend timeline, and did not line up as well with Influenza's.

7 CONCLUSION AND DISCUSSION

To conclude, this study has investigated the COVID-19 pandemic and the corresponding health policies on the patterns of influenza cases. Through empirical analysis we have observed a clear decline in influenza cases coinciding with the COVID-19 pandemic. This trend was noted globally and within individual countries, points to a potential correlation between health measures taken to combat COVID-19 and the decrease in Influenza cases. The LSTM model was used to perform time series forecasting on the Influenza data, providing an estimate of expected case numbers during the years affected by COVID-19. The model was able to accurately capture the cyclic nature of Influenza cases and presented a reasonable prediction of what Influenza case numbers would have looked like without the impact of the COVID-19 pandemic. While this study provides valuable insights, it also identifies the complex interplay of factors that influence disease transmission. The observed decline in Influenza cases could be attributed to a range of factors, including increased hygiene practices, mask-wearing, social distancing, and changes in healthcare-seeking behavior during the COVID-19 pandemic. Understanding these factors in depth could inform better public health strategies for future pandemics. This study opens a few avenues of future work. The first being, the LSTM model could be refined to account for additional variables such as vaccination rates, population density, and specific health policies. It could also be extended to study the impact of COVID-19 on other infectious diseases, providing a broader understanding of the pandemics influence. From our OLS results we know that Public Information Campaigns are crucial to public health. How this can and should be implemented throughout the future is an area of future discussion. A possible route is to factor in the costs associated with each policy and use those to move to a Weighted WLS model.

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