Modeling the impact of vaccination, mask policies and mobility on the COVID-19 pandemic in Singapore

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ABSTRACT

In this project, we will use cutting-edge epidemiology models to study the impact of vaccination, mask policies and mobility on the outbreak of COVID-19 in Singapore.

CCS CONCEPTS

• **Computing methodologies → Model verification and validation**.

1 INTRODUCTION

The outbreak of a new crown outbreak depends on many factors, among which human influences include population mobility patterns, mask prevalence, and vaccination rates. The research in our project addresses the three important factors mentioned above. All three factors are influenced to some extent by government policies, and government decisions can be seen to influence the trend of the epidemic. We selected two outbreak trends in Singapore, which are listed below:

- Singapore, March 2020 to Sept 2020 (optional)
- Singapore, July 2021 till now, mainly delta variant

There are significant differences among these two outbreaks. For example, during the last year's outbreak in Singapore, there were no available vaccines, but the government had published very strict policies to reduce social interactions. And for this year's outbreak in Singapore, nearly 90% of people have been fully vaccinated, but the government is entering the 'Preparatory Stage' and the local restrictions have been relaxed. The difference in vaccination rates and population mobility can help us to make a more accurate analysis of the impact of vaccination, mask policies and mobility. We hope that by studying these three factors and analyzing their weights on the outbreak trends, we can help the government to develop more effective prevention strategies to achieve successful protests. At the same time, we verify whether our research model is reasonable through data to achieve the purpose of accurately predicting the future trend of the epidemic.

2 RESPONSE TO THE COMMENTS OF OUR MILESTONE REPORT

- We add a title for the project.
- We add a SIR ODE model fitting the Singapore data to figure out the range of parameters and perform the calibration in a larger period with more parameters in this project. See the section 5 for details.
- We use optuna to do the calibration in this project on first outbreak and second outbreak of Singapore separately in the period from last year to this years. Calibration details are discussed in section 7.

3 LITERATURE REVIEW

We summarize and outline some information from papers related to agent models, including a new approach to predict the spread of COVID-19 in facilities based on agent models, the COVID-ABS agent model, the impact of the number of masks used globally on the outbreak discussed based on agent models, and the analysis of Australian data based on agent models. One of the emerging approaches based on agent models is used to represent complex systems comprising agents whose behavior is specified using simple rules [2]. This method differs from mathematical analyses of LGBT communities in that it represents individuals with a variety of characteristics, resulting in more realistic results. An agent-based strategy is offered for assessing COVID-19 transmission concerns in facilities. The spatio-temporal transmission mechanism is modeled in this way. Simulating spatio-temporal transmission mechanisms and simulating agents making judgments based on pre-programmed criteria are the foundations of this technology. These rules represent the geographical patterns and infectious situations with which the agents interact to explain the infection process. The model is extremely versatile, allowing for the testing of various hypotheses as well as alternative scenarios by considering hypothetical conditions that cannot be studied in real life. When compared to experimental methods, using this agent-based model offers the advantage of saving time and money. The ABS proxy model [7], which simulates the epidemiological and economic impact of the COVID-19 pandemic in closed societies and whose results can be generalized in a broader context and used by government rulers to predict social policies and evaluate their effectiveness in real-world scenarios, is similar to this. This model creates novel situations by taking into account the unique characteristics of several research areas. The future study hopes to improve the model by incorporating methods for closing and opening organizations, as well as the ability to fire workers. Based on various scenarios as well as government planning, the model can potentially be optimized as a library. In another paper [3], the movement of ABS agent models to predict the effect of masking on virus transmission is also mentioned in the literature. The paper compared two different pandemic viruses, including the recent COVID-19, based on this agent-based model, and the researchers

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compared the model's predictions with a large body of data to show a strong correlation between mask-wearing and the increase and decrease in daily cases. Fine-grained computational simulations [1] of the pandemic were generated for Australia based on an agent model, and strategies to control for COVID-19 mitigation and suppression were introduced from the simulation data results, which were calibrated to match key features of COVID-19 transmission, with an important calibration result being the age-related scores of symptomatic cases. Above we have discussed and referred to some new technologies about the application of the proxy model and the impact of using this model on the trend of wearing masks on the pandemic and the prediction application based on Australian data and proxy models. These favorable information and analysis are useful for our project. Progress has helped a lot and brought us more ideas.

4 DATA SOURCE

The data source for this study are listed below, which is also available at this link. For a quick overview, Figure 1 shows the daily confirmed COVID-19 cases/deaths and Google (residential) mobility trends of Singapore from February 17th 2020 to Oct 29th 2021.

- COVID-19 cases/deaths/vaccines: The COVID-19 related data comes from data.world. We choose several data points and verify it with official MOH report. For the missing vaccine data (from Jan 11th 2021 to June 30th 2021), we fill it with data from Our World in Data and perform linear interpolation to make it continuous.
- Epidemiology: The epidemiology data of COVID-19, such as duration parameters (for example, duration between exposed state and infectious state), age-linked disease probability (for example, relative susceptibility to infection), is built in the library covasim.
- Demographics: The population age distribution data comes from this Github repo and is built in the library covasim. However, because the Department of Statistics of Singapore only releases the resident population age distribution, we are not able to verify the correctness of this data.
- Mobility: We use Google Community Mobility Reports as the indicator of mobility. The reports provide the changes in movement trends across different categories of activities, which includes residential, retail and recreation, groceries and pharmacies, parks, transit stations, and workplaces. We collect this data from Our World in Data.
- Policy: We use mask policy indicator, which is categorized into five categories: 0 - no policy; 1 - recommended; 2 - required in specified public spaces; 3 - required in all public spaces; 4 - required outside the home at all times. We also collect other relevant policy data (such as quarantine policy, face covering policy) from official MOH report.

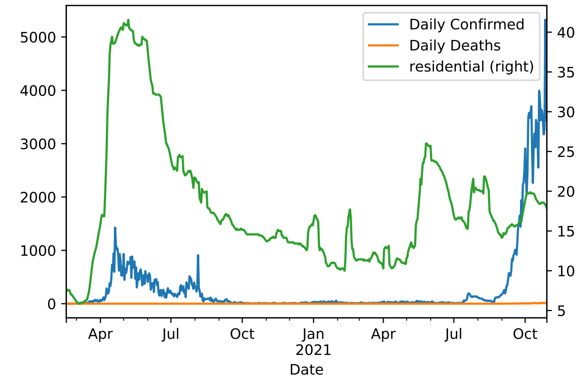

Figure 1: Daily COVID-19 counts and Google mobility trends

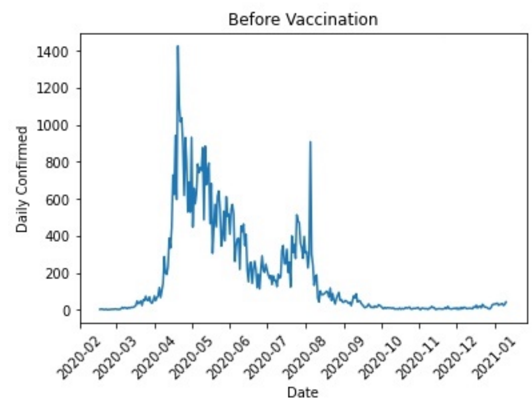

Figure 2: Daily Confirmed before vaccination

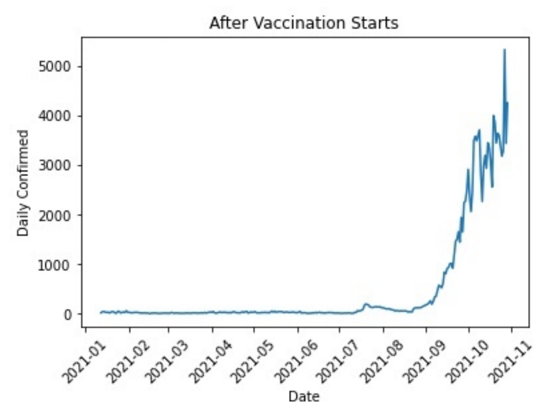

Figure 3: Daily Confirmed after vaccination

5 ODE MODEL

In this section, we use the simple SIR ODE model to fit the COVID-19 data in Singapore as a supplement to our complicated agent-based model and to get a basic idea about the ranges of the parameters.

5.1 Background and domain research

First we plot the daily confirmed data before and after vaccination to have an intuitive understanding on the outbreaks of COVID-19 in Singapore (Figure 2 and Figure 3).

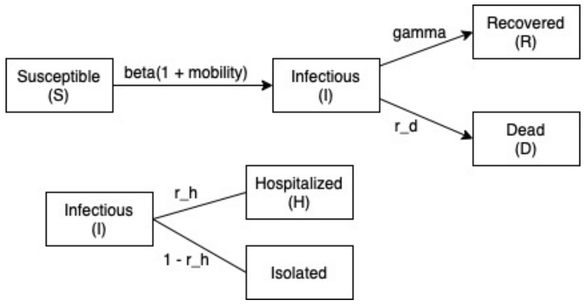

Figure 4: Flow Diagram of our SIR model

As the daily confirmed infectious data shows, there are mainly three outbreaks: the first peaks around May 2020, and the second starts from September 2021.

The outbreak around May 2020 according to the news report and the statistics data provided by the Ministry of Health (MOH) Singapore , happens mainly among the foreign workers who live in the crowded dorms. The outbreak starts from September 2021 is caused by Singapore's new policy that treats COVID-19 in the way of treating flu, including opening the board and canceling the guarantee requirements for specific travelers, which loosens the intervention upon the COVID-19 to a great extent and causes a wide spread in communities.

The first outbreak and the second outbreak happened in different vaccination and policy backgrounds. Thus if we want to get the effectiveness of vaccination upon the outbreak, at least we need to integrate the effectiveness of policy into my ODE equations.

5.2 Model Description

Because all infectious cases, including asymptomatic infectious cases and cases in incubation periods are also counted to the confirmed cases and are required isolation, we remove the exposed states in SEIR model and use the SIR model instead.

There are four compartments in our ODE model, with the Infectious comprising two states - Hospitalized and Isolated. Below is the flow among the compartments (See Figure 4 and the ODE equations).

$$\begin{cases} ds/dt = -\beta S(t)I(t)(1 + mobility(t)/100)/N \\ di/dt = \beta sI(t)(1 + mobility(t)/100)/N - \gamma I(t) - (I)r_d \\ dd/dt = I(t)r_d \\ dh/dt = di/dt \times r_h \\ dr/dt = \gamma I(t) \end{cases} \tag{1}$$

The Singapore COVID-19 dataset we get includes the basic datas that are related to the COVID-19 contamination in a region and its policies to intervene in the COVID-19. However data likes the exact number of confirmed infectious cases and the number of the hospitalized people are not enough to directly measure specific states in ODE model. And due to factors like testing policies and statistical granularity, there might be inaccurate or missing data. Thus we researched Singapore's COVID-19 policies and the statistical report provided by the MOH and found proper statistical data for S, I, R states.

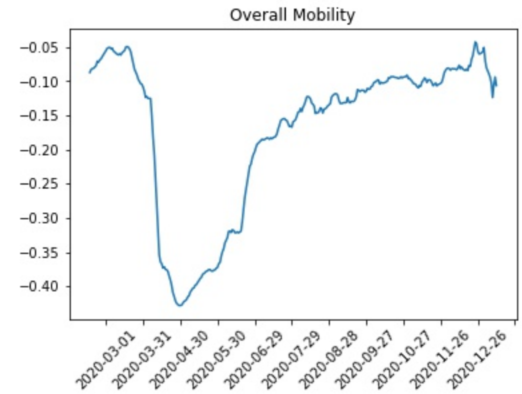

Figure 5: Mobility Before Vaccination

For the S states, I first set S = Population - I - R.

For the I states, we set I = Intensive Care Unit (ICU) + General Wards + In Isolation. This is the way MOH uses to calculate the number of the active infectious cases. And thanks to Singapore's strict social lockdown and tracking spread policies, this data is accurate enough to reflect the infectious situation.

For the R states, we set R = Cumulative Confirmed - Cumulative Death - I.

5.3 Model fitting

We use the minimize function in lmfit module (Non-Linear Least-Squares Minimization and Curve-Fitting), which implements the Levenberg-Marquardt algorithm to minimize the error between the measured data and the fitted data. At the start, we set the error as below, where m indicates measured and f indicates fitted.

$$error = \sum_t \{(St_m - St_f)^2 + (It_m - It_f)^2 + (Rt_m - Rt_f)^2 + (Dt_m - Dt_f)^2\}^{1/2} \tag{2}$$

The problem within such residual can include:

- Trying to minimize the error for fitting three curves at the same time leads to failure in every single curve.
- The absolute error for different curve is quite different. The value of S is much bigger than the value of I and the value of R thus it should allow bigger absolute error.

Thus we changed my fitting method to fit only one curve for one iteration. First we fit the Infectious curve, and then the death curve and the recovery curve.

After one iteration of fitting, we found it's hard to fit the infectious curve because the rate of Suspicious almost remains unchanged due to the sparsity of infectious case and the strict social lockdown policy in Singapore. With the s / N remains approximately 1, di/dt = beta * i (1+ mobile[t]) - gamma * i - rd * i and whether di/dt > 0 or di/dt < 0 is only influenced by mobile[t] (The mobility data is shown in Figure 5 and 6).

So after reading some papers who fit SEIR and SIR model to the real dataset, we decide to narrow the clique of COVID-19 spread in Singapore and set the total number of people rather than the

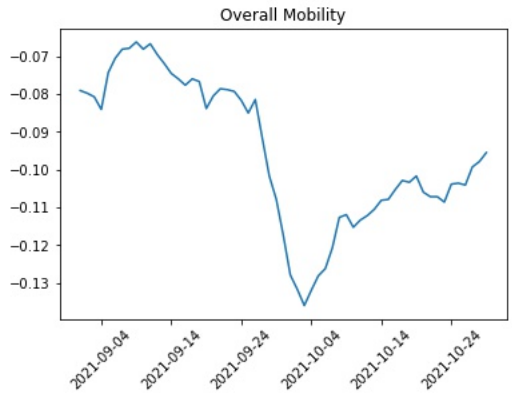

Figure 6: Mobility After Vaccination

population of Singapore, but instead as 110000 who are possible to engage in the spread and the number of the susceptible as 90000, and get a good fit.

5.4 Observations

As the fit results indicate, the beta of the first outbreak (May 2020) is 0.44964359, while the beta of the second outbreak (September 2021) is 0.18322612. With a more loose overall policy, the second outbreak still gain a better beta, which indicates that the vaccine has effectively prevented the spread of COVID-19.

6 AGENT-BASED MODEL

In this section, we provide a formal description of covasim model [4] and how we model vaccinations, mask policies and mobility changes within our model.

6.1 Disease progression

In covasim, the disease state of an agent is characterized as susceptible, exposed, infectious (asymptomatic, presymptomatic, mild, severe, critical), recovered and dead. The Figure 7 shows all possible transformation between any two disease states. Each transformation is also parameterized with a probability p (how likely does the transformation happen) and a duration τ (how long does the transformation take). The age-linked value of p and the distribution of τ are detrived from lots of previous research and are built in covasim.

6.2 Contact network

To model the contact network between people, covasim assigns people to four network layers: household, school, workplace and community. More specifically, covasim generates a population of people based on the location-specific age distribution. After that, covasim assigns people aged between 6 and 22 to schools, assigns people aged between 22 and 65 to workplaces and assigns people to households based on the location-specific household size.

Within each network, the contact number of each person is sampled from poisson distributions. For each contact between a susceptible individual and an infectious individual, the probability of a successful virus transmission is β.

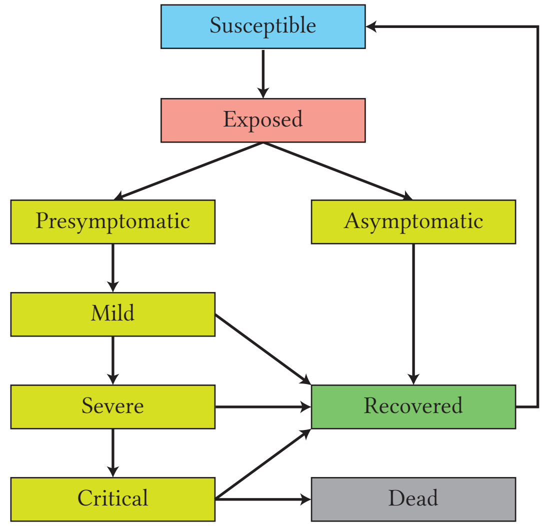

Figure 7: Covasim model, disease state transformation structure

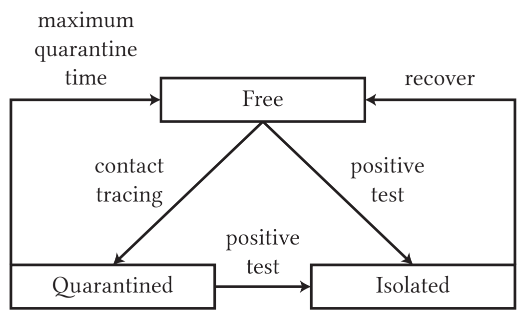

Figure 8: Covasim model, agent state transformation structure

6.3 Agent states

One important feature of covasim is that it provides several useful agent states so that it can describe testing, contact-tracing, quarantine and isolation policies. Figure 8 lists out built in agent states and transformations between them.

- Free: If an agent is free, the agent has 100% β value. If a free agent has a contact with a confirmed case and is traced successfully, the agent will become quarantined. If a free agent has positive test results, the agent will become isolated.
- Quarantined: If an agent is quarantined, the agent has 60% β in the household layer and 20% β in other layers. The quarantine ends when it reaches the maximum quarantine time. However, if a quarantined agent has positive test results, the agent will also get isolated.
- Isolated: If an agent is isolated, the agent has 30% β in the household layer and 10% β in other layers. A isolated agent will become free once the agent recovers.

6.4 Mask policies and mobility

There are two important factors which affect the spread of COVID-19. The first one is personal protection, such as wearing masks, washing hands, etc, which reduces the probability of virus transmission per contact, i.e., the β value The second one is social distancing, such as avoiding crowds, keeping distance from others, staying at home, etc, which reduces the contact number of each agent.

Within our model, we use mask policies and mobility to represent personal protection and social distancing respectively. More specifically, denote numerical mask policies and mobility as $x_{\text{ma}}, x_{\text{mo}}$, we define a function $f : \mathcal{R}^2 \rightarrow [0, 1]$ as:

$$f(x_{\text{ma}}, x_{\text{mo}}) = \frac{2(a_1 x_{\text{ma}} + b_1)(a_2 x_{\text{mo}} + b_2)}{(a_1 x_{\text{ma}} + b_1) + (a_2 x_{\text{mo}} + b_2)} \tag{3}$$

We can view this function as first applying two linear transformation on $x_1 = a_1 x_{\text{ma}} + b_1$, $x_2 = a_2 x_{\text{mo}} + b_2$ and then apply the function $g(x_1, x_2) = 2x_1x_2/(x_1 + x_2)$. We can view the function g in another way:

$$\begin{aligned} g(x_1, x_2) &= \frac{2x_1x_2}{x_1 + x_2} \\ &= \min\{x_1, x_2\}\frac{\max\{x_1, x_2\}}{x_1 + x_2} + \max\{x_1, x_2\}\frac{\min\{x_1, x_2\}}{x_1 + x_2} \end{aligned} \tag{4}$$

We design such function because we believe that the smaller value of x_1, x_2 has a larger impact of β. After that, for each day we calculate the β value as $f(x_{\text{ma}}, x_{\text{mo}})\beta_0$, where the β_0 is a constant within one outbreak (for a variant of SARS-CoV-2) and $x_{\text{ma}}, x_{\text{mo}}$ changes each day.

7 AGENT-BASED MODEL RESULTS

7.1 Calibration process

We use optuna to perform the calibration. Each time, we sample parameters from the Tree-structured Parzen Estimator (TPE) sampler and run the simulation once. After that, we calculate the minimization objective value as the mean absolute error of the cumulative confirmed number between the simulation results and the real-world data and feed the objective value to sampler. Because of the limitation of hardware and time, we times all the cases/deaths/vaccines with 0.01. We use the negative of mask policy indicator and the negative of residential mobility as the numerical mask policies and mobility value. We model the first outbreak (from March 2020 to Sept 2020) and the second outbreak (from July 2021 to Oct 25th) separately because they are caused by different variants.

For the first outbreak, we calibrate the following parameters:

- β_0: the probability of a successful virus transmission per contact, calibration range is $[0.06, 0.10]$.
- ma_{min}: we calculate a_1 and b_1 such that $\max\{a_1x_{\text{ma}}+b_1)\} = 1.0$ and $\min\{a_1x_{\text{ma}} + b_1)\} = \text{ma}_{\text{min}}$. The calibration range is $[0.03, 0.25]$.
- mo_{min}: we calculate a_2 and b_2 such that $\max\{a_2x_{\text{mo}}+b_2)\} = 1.0$ and $\min\{a_2x_{\text{mo}} + b_2)\} = \text{mo}_{\text{min}}$. The calibration range is $[0.1, 0.6]$.
- symp_prob: the test probability of a symptomatic agent, calibration range is $[0.9, 1.0]$.
- trace_probs: the successful probability of a contact tracing, calibration range is $[0.75, 0.99]$.
- start_shift: the number of days between the first ten people get infected and the first confirmed case, calibration range is $[-8, 8]$.

Besides these parameters, we set the following parameters as constants:

- pop_infected = 10: the number of infected people at the start of the simulation
- asymp_prob = 0: the test probability of a asymptomatic agent
- quar_period = 7: the maximum quarantine time in days, we collect the value from the official MOH website
- test_delay = 1: the number of days for test results to be known

After calibrating the first outbreak, we setup the second outbreak with the same constants and the calibration results ma_{min}, mo_{min}, symp_prob, trace_probs of the first outbreak. For the second outbreak, we only calibrate the β_0 value in range $[0.61, 0.3]$ and the start_shift in range $[-21, 21]$ while take the vaccinations into consideration. Instead of introducing infected populations at the start of the simulation, we introduce 10 people infected by delta variant on the day when the first case gets confirmed (24th August) shifted by start_shift.

Regards the vaccination, we assume that people only receive Pfizer COVID-19 vaccines and the order in which people get vaccinated is the descending order of people's age. We also assume that people who have received the first dose 21 days before have priority in receiving the second dose. We calibrate the first outbreak with 5000 samples and the second outbreak with 2000 samples.

After calibrating the second outbreak, we assume the daily vaccine doses, mask policies and mobility as the mean of the last 30 days and predict the epidemiology data of the next 30 days, which lies in the yellow area of Figure 10.

7.2 Calibration results

For the first outbreak, the calibrated parameters are $\beta_0 = 0.061$, $\text{ma}_{\text{min}} = 0.13$, $\text{mo}_{\text{min}} = 0.43$, symp_prob = 0.9, trace_prob = 0.79, start_shift = 3. Figure 9 shows the calibration results of the first outbreak. The calibration results fit the data pretty well except the first month, which may results from the relatively low testing probability at the beginning.

For the second outbreak, the calibrated parameters are $\beta_0 = 0.134$, start_shift = 10. Figure 10 shows the calibration results of the first outbreak and the prediction of the next 30 days (in yellow area). The calibration results not only fit the data well but also give a pretty good prediction. Cause the β_0 value has already been multiplied by 2.2 within covasim, the real β_0 value is $2.2 \times 0.134 \approx 0.295$, which is about four times larger than the β_0 value of the first outbreak.

7.3 Effect of vaccination

To evaluate the effect of the vaccination, we run the simulation of the second outbreak with same parameters but without vaccination. Figure 11 indicates that more than a half of the total population will get infected under such mask policies and mobility, which reveals the importance of the vaccination.

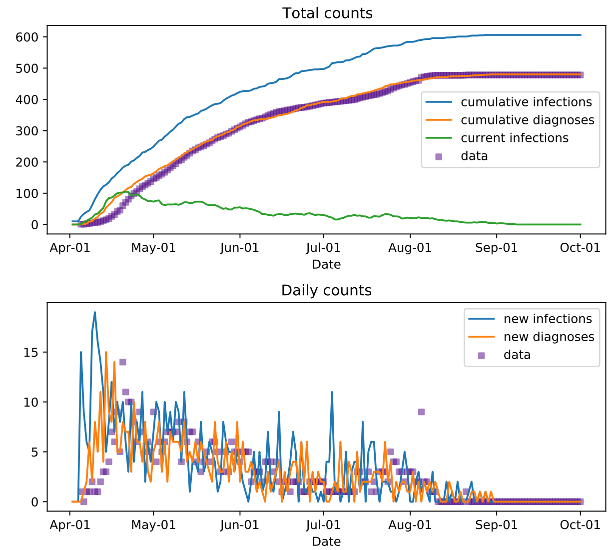

Figure 9: First outbreak, calibration results

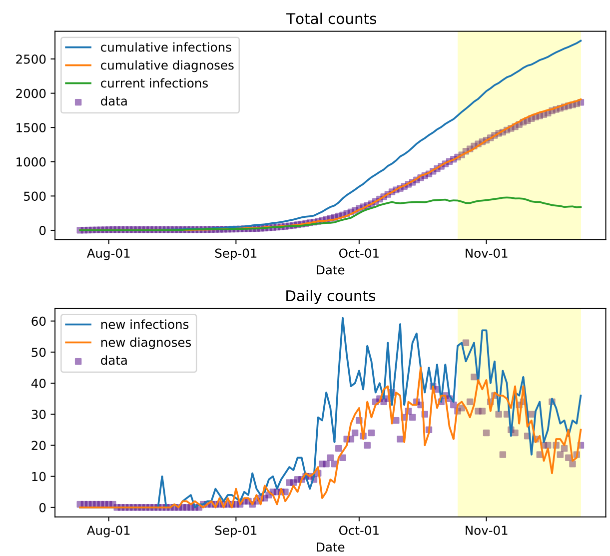

Figure 10: Second outbreak, calibration results

7.4 Effect of mask policies and mobility

Figure 12 shows the impact of mask policies and mobility on the β value. When the mask policies are not strict, the change of mobility explains the main part of the change of β. However, when the mask policies becomes strict after mid-April, the change of mobility only causes small fluctuations on β.

8 CONCLUSION AND DISCUSSION

8.1 ODE model

The fitting method still needs improvement. For the fitting iterations, we only involve infectious data in residual function and

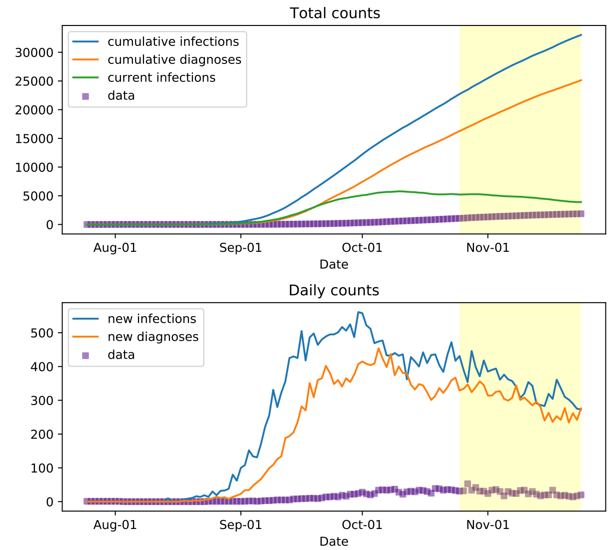

Figure 11: Second outbreak, without vaccination

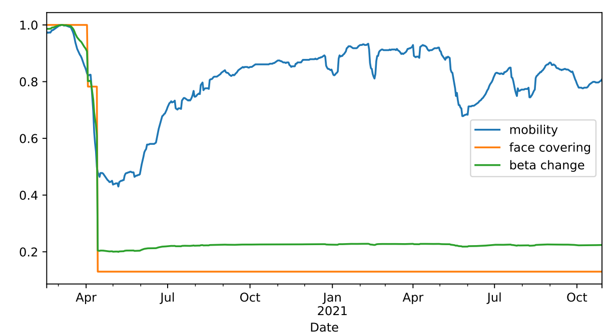

Figure 12: The impact of mask policies and mobility

minimize the error in fitting the infectious data to get an initial beta. Then we use the beta for following iterations for minimizing the error in fitting the death data and then the hospitalized data and then the recovery data. The beta doesn't change much during the iterations. For example, for the after vaccine outbreak, the beta after each iteration is : 0.18322830 -> 0.14602370 -> 0.20936286 -> 0.26362917. Though the beta doesn't change much during these iterations, every iteration fits the assigned curve well but doesn't perform as well in other curves (see Figure 13). So it is still not scientific enough to fit for only one parameter and one curve for one iteration. It would be better if all the curves are fitted at the same time in every iteration.

Another point for improvement is to find a scientific way to measure and estimate the number of susceptible cases in real life spread. We get a good fit result by manually assigning the number of initial susceptible cases and we also see other researchers who set the number of initial susceptible cases as a value suggested by domain experts. So it would be very helpful for using the SIR and SEIR ODE model to research on real life problems if there is a more

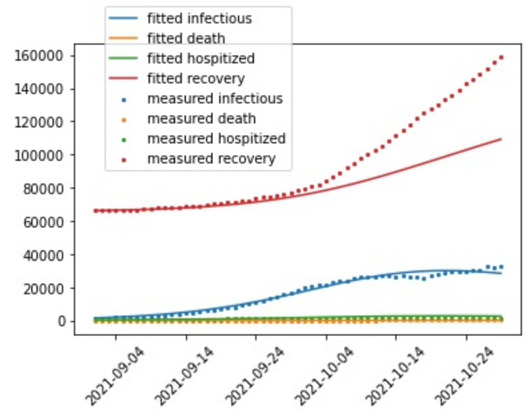

Figure 13: Fitting Results of the Second Outbreak

systematic and scientific method to get the number of S state cases in real life.

8.2 Agent-based model

The results of the agent-based model reveal the importance of vaccination and strict mask policies. Even the delta variant is highly infectious, with vaccination and strict mask policies the number of infections is still able to be controlled small. The mobility takes an important role when mask policies are relatively loose but contributes little to the spread of COVID-19 when mask policies are strict. Therefore, we strongly suggest that high vaccination rate and strict mask policies are vital for fighting against COVID-19.

However, there are several aspects that may be improved in the future research.

First, we assume that lots of parameters are constant within out model, such as test probability, contact tracing probability, quarantine period, etc. However, these parameters changes during the pandemic and highly depends on the government policies and the pandemic situation. Future research can focus on how the model the change of these parameters so that the model can represent the reality better.

What's more, covasim calculates the waning effect of vaccines based on the decreasing of neutralizing antibody [5] and calculates the effectiveness against the delta variant based on this paper [6]. Because of limited time and knowledge, we are not able to verify the correctness of these values and models. The waning effect of vaccines and the effectiveness against different variants are hot topics in this area. We should also notice that Singapore has started the vaccine booster program from October 1st while the impact of the booster is still under research. Therefore, future research may be able to model the effectiveness of vaccines in a more accurate way.

9 APPENDIX

Code and datasets for this project are available at this Github repo.

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CSE 8803-EPI Project Milestone Report

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ABSTRACT

In this project, we will use cutting-edge epidemiology models to study the outbreak of COVID-19 in Singapore and Taiwan, taking into account the vaccination progress, the decline of vaccine effectiveness and the local government policies.

CCS CONCEPTS

• **Computing methodologies → Model verification and validation**.

1 INTRODUCTION

In this project, we will mainly focus on three outbreaks of COVID-19:

- Taiwan, May 2021 to Aug 2021, mainly delta variant (optional)
- Singapore, March 2020 to Sept 2020 (optional)
- Singapore, July 2021 till now, mainly delta variant

There are significant differences among these three outbreaks. For example, during the last year's outbreak in Singapore, there were no available vaccines, but the government had published very strict policies to reduce social interactions. And for this year's outbreak in Singapore, nearly 90% of people have been fully vaccinated, but the government is entering the 'Preparatory Stage' and the local restrictions have been relaxed. Through analyzing and modelling the three outbreaks, we are looking forward to answering several questions (or a part of them):

- How does the vaccination affect the outbreak?
- How does the decline of vaccine effectiveness affect the outbreak? Will the vaccine booster help stopping the current outbreak in Singapore?
- How does the government policy affect the outbreak?

Furthermore, we will evaluate our models from two aspects:

- whether the model is able to explain past data, especially the current outbreak in Singapore
- whether the model is able to predict the future COVID-19 situation of Singapore

2 RESPONSE TO THE COMMENTS OF OUR PROPOSAL

- We have added several papers in the next section, which are related agent-based models, optimization and vaccine effectiveness.
- Taiwan CDC provides confirmed case number per county while Singapore MOH doesn't provide more localized data. We may further study Taiwan COVID-19 data if time permitted.
- Singapore MOH provides contact tracing data (only linked to the COVID-19 clusters) and places visited by cases (not linked to the case number), but they doesn't provide the network of people. We won't learn the relationship between any two person unless one is infected by the other. Therefore, we are not able to estimate missing infections.

3 FURTHER LITERATURE REVIEW

3.1 Agent-based models

We summarize and outline some information from papers related to agent models, including a new approach to predict the spread of Covid-19 in facilities based on agent models, the Covid-ABS agent model, the impact of the number of masks used globally on the outbreak discussed based on agent models, and the analysis of Australian data based on agent models.

One of the emerging approaches based on agent models is used to represent complex systems comprising agents whose behavior is specified using simple rules [3]. This method differs from mathematical analyses of LGBT communities in that it represents individuals with a variety of characteristics, resulting in more realistic results. An agent-based strategy is offered for assessing COVID-19 transmission concerns in facilities. The spatiotemporal transmission mechanism is modeled in this way. Simulating Spatio-temporal transmission mechanisms and simulating agents making judgments based on pre-programmed criteria are the foundations of this technology. These rules represent the geographical patterns and infectious situations with which the agents interact to explain the infection process. The model is extremely versatile, allowing for the testing of various hypotheses as well as alternative scenarios by considering hypothetical conditions that cannot be studied in real life. When compared to experimental methods, using this agent-based model offers the advantage of saving time and money. The ABS proxy model [7], which simulates the epidemiological and economic impact of the COVID-19 pandemic in closed societies and whose results can be generalized in a broader context and used by government rulers to predict social policies and evaluate their effectiveness in real-world scenarios, is similar to this. This model creates novel situations by taking into account the unique characteristics of several research areas. The future study hopes to improve the model by incorporating methods for closing and opening organizations, as well as the ability to fire workers. Based

*All authors contributed equally to this research.

on various scenarios as well as government planning, the model can potentially be optimized as a library.

In the other paper, the movement of ABS agent models to predict the effect of masking on virus transmission is also mentioned in the literature[4]. The paper compared two different pandemic viruses, including the recent COIVD-19, based on this agent-based model, and the researchers compared the model's predictions with a large body of data to show a strong correlation between mask-wearing and the increase and decrease in daily cases. Fine-grained computational simulations of the pandemic were generated for Australia based on an agent model, and strategies to control for COIVD-19 mitigation and suppression were introduced from the simulation data results, which were calibrated to match key features of COVID-19 transmission, with an important calibration result being the age-related scores of symptomatic cases [2].

Above we have discussed and referred to some new technologies about the application of the proxy model and the impact of using this model on the trend of wearing masks on the pandemic and the prediction application based on Australian data and proxy models. These favorable information and analysis are useful for our project. Progress has helped a lot and brought us more ideas.

3.2 Optuna

After we build the simulation model of COVID-19 outbreaks, there are several approaches to accomplish the calibration. The most primary way is to use optimization modules like sciPy to do the standardized calibration with the loss value of the model fit. Also, there are more advanced methods to do the calibration like the adaptive stochastic descend method of the Sciris library, or Bayesian approaches such as history matching, and sequential Monte Carlo methods. However, the author of the model we adopted suggests that Optuna is the approach that suits this model best, so we get to read papers about Optuna.

The paper [1] talks about the implementation of the hyperparameter optimization, which is what we currently use to calibrate our simulator model. So the research on hyperparameter optimization can help us better understand the principle of this kind of calibration and evaluate if it is proper for our simulator model case. Furthermore, if it is the best approach for the calibration of our model, we can get to know how to improve the performance of this calibration algorithm.

The hyperparameter optimization basically consists of two parts that contribute most to improving its cost-effectiveness - one is the searching strategy for choosing parameters to investigate, the other is the performance estimation strategy that decides which parameters should be discarded during the process of optimization.

For both the searching strategy and the performance evaluation strategy part, the method of sampling the parameter is very important for effectiveness. The Optuna is using a combination of relational sampling that exploits the correlations among the parameters and independent sampling that samples each parameter independently. To better meet our demand, we can also import or customize our own method to do the hyperparameter sampling.

For the performance evaluation strategy part, there are generally two phases of pruning. In Optuna, 'report API' is responsible for in phase 1 to the monitoring functionality, and 'should prune API' is responsible in phase 2 for the premature termination of the unpromising trials. The background algorithm of the 'should prune' method is implemented by the family of pruner classes.

Above is the core algorithms of Optuna which indicates what we can do to modify and customize this hyperparameter optimization for our model.

3.3 Delayed second vaccine dose

Since our purpose is to evaluate the influences vaccination and the decline of vaccine effectiveness exert on the outbreak of COVID-19, we need to know which parameters might reflect the influences of vaccine and the decline of vaccine effectiveness from a biological perspective and from an epidemiological perspective.

According to the agent-based model in this paper [6], the risk of infection for people susceptible to COVID-19 depended on contact with infectious individuals that could be in asymptomatic, presymptomatic, or symptomatic stages of the disease.

This model mainly researches the influence of the DSD(a 9-week delayed second dose). The research team made two experiments based separately on the premise of the vaccination with waning efficacy and without waning efficacy. The result shows that if the efficacy of the first dose did not wane until the administration of the second dose, then the DSD strategy will be more effective than the recommended schedules for both Pfizer-BioNTech and Moderna vaccines. If the efficacy of the first dose wanes over time, delaying the second dose of Moderna vaccines could prevent more infections, hospitalizations, and deaths compared to the recommended 4-week interval between the 2 doses.

This model does not directly provide us with the information of the decline of the vaccine and its influence, it inspires us to find the efficacy of the vaccine in published studies of clinical trials, FDA briefing documents, and vaccination campaigns. Also, it figures out the two most important parameters to evaluate the efficacy of vaccines: the durability of vaccine efficacy and the ability of vaccines to block transmission.

4 MODEL DESCRIPTION

In this section, we provide a formal description of covasim model [5].

4.1 Disease progression

In covasim, the disease state of a agent is characterized as susceptible, exposed, infectious (asymptomatic, presymptomatic, mild, severe, critical), recovered and dead. The Figure 1 shows all possible transformation between any two disease states. Each transformation is also parameterized with a probability p (how likely does the transformation happen) and a duration τ (how long does the transformation take). The value of p and the distribution of τ are detrived from lots of previous research and are built in covasim.

4.2 Contact network

To model the contact network between people, covasim assigns people to four network layers: household, school, workplace and community. More specifically, covasim generates a population of people based on the location-specific age distribution. After that, covasim assigns people aged between 6 and 22 to schools, assigns

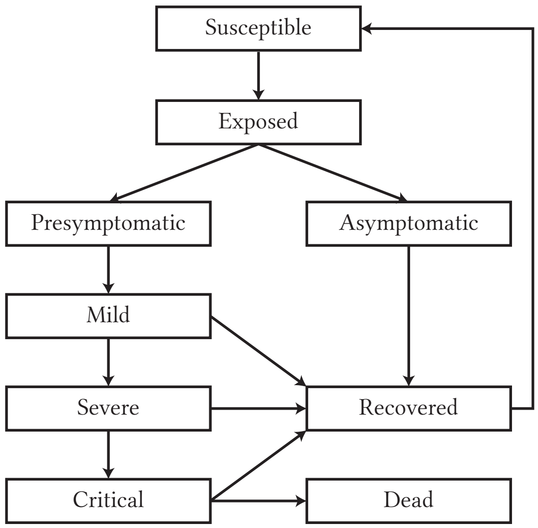

Figure 1: Covasim model, disease state transformation structure

people aged between 22 and 65 to workplaces and assigns people to households based on the location-specific household size. Within each network, the contact number of each person is sampled from poisson distributions by default.

4.3 Intervention

One important feature of covasim is that it provides several useful interventions and supports customized interventions. Figure 2 lists out built in agent states and transformations between them.

- Free: If a agent is free, the agent has 100% beta value.
- Quarantined: If a agent has a contact with a confirmed case and is traced successfully, the agent will become quarantined, which has 60% beta in the household layer and 20% beta in other layers.
- Isolated: If a agent has positive test results, the agent will become isolated, which has 30% beta in the household layer and 10% beta in other layers.

Besides transformations between agent states, covasim also supports the vaccine intervention. The vaccinated agents will have lower probability of getting infected and developing symptoms. The waning effectiveness and the different effectiveness against variants are also built in covasim.

5 DATA COLLECTION

5.1 Collection process

- COVID-19 cases/deaths/vaccines: The COVID-19 related data comes from data.world. We choose several data points and verify it with official MOH report. For the missing vaccine data (from Jan 11th 2021 to June 30th 2021), we fill it with data from Our World in Data and perform linear interpolation to make it continuous.
- Epidemiology: The epidemiology data of COVID-19, such as duration parameters (for example, duration between exposed state and infectious state), age-linked disease probability (for example, relative susceptibility to infection), is built in the library covasim.
- Demographics: The population age distribution data comes from this Github repo and is built in the library covasim. However, because the Department of Statistics of Singapore only releases the resident population age distribution, we are not able to verify the correctness of this data.
- Mobility: We use Google Community Mobility Reports as the indicator of mobility. The reports provide the changes in movement trends across different categories of activities, which includes residential, retail and recreation, groceries and pharmacies, parks, transit stations, and workplaces. We collect this data from Our World in Data.
- Policy response: We use Stringency index, a "composite measure based on nine policy response indicators" rescaled to a value from 0 to 100, as the indicator of the government policy. We also collect relevant data (such as quarantine policy, face covering policy) from official MOH report.

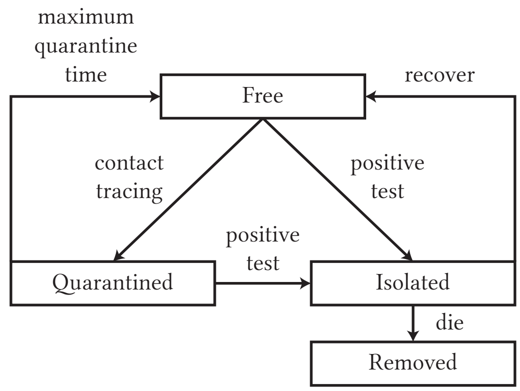

Figure 2: Covasim model, agent state transformation structure

5.2 Initial findings

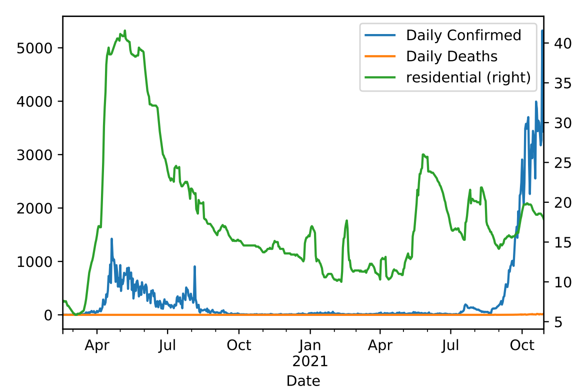

Figure 3: Daily COVID-19 counts and Google mobility trends

Figure 3 shows the daily confirmed COVID-19 cases/deaths and Google (residential) mobility trends of Singapore from February 17th 2020 to Oct 19th 2021. The residential mobility shows the changes of stay-at-home activities, which can be viewed as the prevent of the spread of COVID-19. Several initial findings from the Figure 3 and the data are listed below:

- The first outbreak lasts from from Feb 17th 2020 to Oct 1st 2020. The second outbreak lasts from July 1st 2021 till now.s
- The number of deaths is relatively small, especially during the first outbreak. Thus, we will calibrate the model with the number of (confirmed) cases instead the number of deaths.
- Although the residential mobility drops a lot from June 2020 to February 2021, the number of daily confirmed cases doesn't increase as expected, which may result from the strict face covering policy.
- There is a small fluctuation of the number of daily confirmed cases around August 2020, which may result from the throughout COVID-19 testing for all dormitories housing foreign workers finishing by first week of August.

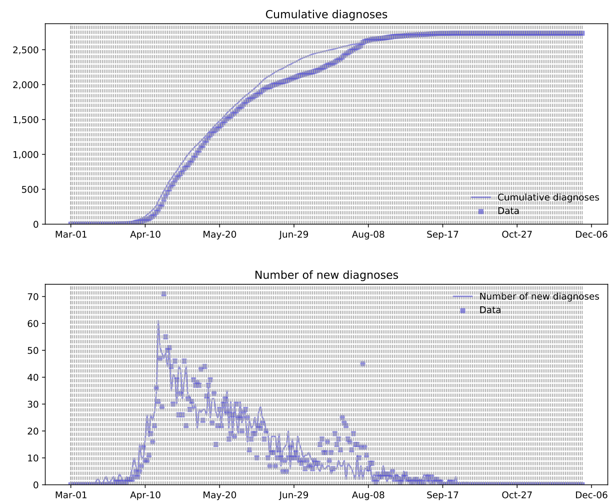

Figure 4: Calibrated simulation result vs Real-world data

6 TEMPORARY RESULT

6.1 General difficulties

- The model is extremely sensitive to parameters (such as beta, the influence of mobility on beta, COVID test accuracy, the number initial infectious people, etc). As a result, it is hard to calibrate the model to the right parameters.
- The relatively large number of population will exhaust the RAM space provided by Colab (about 12 GB). As a result, we only simulate 5% of the total population and perform such rescale on the real-world data as well.

6.2 Simulation results

Figure 4 shows the calibrated simulation results and the real-world data of Singapore from March 1st, 2020 to December 1st 2020. The model explains the data very well and smooths the fluctuation we mentioned before automatically.

The notebook for data cleaning is available at data_sg.ipynb. The notebook for simulation and calibration is available at simulation.ipynb.

6.3 Future work

- Use Optuna to calibrate parameters other than beta, such as the influence of mobility/face covering on beta
- Calibrate the model with this year Singapore/Taiwan data (i.e., with the delta variant and vaccines)

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CSE 8803-EPI Project Proposal

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ABSTRACT

In this project, we will use cutting-edge epidemiology models to study the outbreak of COVID-19 in Singapore and Taiwan, taking into account the vaccination progress, the decline of vaccine effectiveness and the local government policies.

CCS CONCEPTS

• **Applied computing → Health informatics**.

1 PROBLEM DESCRIPTION

In this project, we will mainly focus on three outbreaks of COVID-19:

- Taiwan, May 2021 to Aug 2021, mainly delta variant (optional)
- Singapore, March 2020 to Sept 2020 (optional)
- Singapore, July 2021 till now, mainly delta variant

There are significant differences among these three outbreaks. For example, during the last year's outbreak in Singapore, there were no available vaccines, but the government had published very strict policies to reduce social interactions. And for this year's outbreak in Singapore, nearly 90% of people have been fully vaccinated, but the government is entering the 'Preparatory Stage' and the local restrictions have been relaxed. Through analyzing and modelling the three outbreaks, we are looking forward to answering several questions (or a part of them):

- How does the vaccination affect the outbreak?
- How does the decline of vaccine effectiveness affect the outbreak? Will the vaccine booster help stopping the current outbreak in Singapore?
- How does the government policy affect the outbreak?

Furthermore, we will evaluate our models from two aspects:

- whether the model is able to explain past data, especially the current outbreak in Singapore
- whether the model is able to predict the future COVID-19 situation of Singapore

2 LITERATURE REVIEW

2.1 Mathematical model

2.1.1 SEIR multiplex network model [2]. This paper discusses how to accurately predict the development and spread of epidemics. The government needs to formulate corresponding policies based on the spreading effect and development of the epidemic. However, there are many factors leading to the development of the epidemic, and these factors are intertwined. Simple prediction models cannot accurately predict and demonstrate the true situation of the spread of epidemics.

This paper proposes a method of combining multiplex networks and time networks with SEIR models to accurately predict the spread of epidemics in different communities and environments. The researchers divide the spread of the epidemic into two types: short-term contact and long-term contact, including family network, worker dormitory network, workplace network, temporal crowd network, and temporal social gathering network. Researchers combine these networks that simulate real-world social models to generate multiplex networks and temporal networks. By applying such multiplex networks to the SEIR prediction model, the flow of people in different communities can be simulated more accurately. In this way, accurate prediction results can be obtained, also the conclusions derived in this way can be used to study other different complex communities.

However, this research is not complete. The accurate prediction results obtained from the experiment can only show the feasibility of combining multiple networks with the SEIR model because the real-world epidemic transmission factors are more complicated. In addition to the simulated network listed, imported cases from abroad and government policies will also have a great impact on the development of the epidemic, and these factors are not taken into account. Hence the results of the experiment are not completely accurate. Researchers need to simulate more complex social structures to get more accurate prediction results.

2.1.2 Model with vaccinated population[4, 7]. In addition to the limitations of multiple networks mentioned above, there are some factors that can lead to forecast errors. As the world fights against the epidemic for longer and longer, researchers have learned more and more about the virus. Now several vaccines against the virus have been developed. Therefore, the percentage of the vaccinated population in the total population and the effects of different vaccines. The effective rate of different types of viruses will also have a great impact on the prediction of epidemics.

In order to explore the impact of vaccination rate and vaccine efficiency on the trend of the epidemic, we found relevant papers discussing the impact of vaccination on the recovery of social function in the United States. This paper [7] focuses on the coverage of the vaccine population and the effective rate of action of the vaccine, combined with the dynamic zoning model, and expands this model, predicting the role of the proportion of the vaccine population on the future trend of the United States to restore social function. However, the limitation of this paper is that it does not study the risk of infection in different age structures, and it does not

*All authors contributed equally to this research.

take into account the efficiency of the vaccine against the mutant virus.

In view of the limitation of age structure, we found another paper discussing the impact of adult vaccination in Morocco [4]. This article uses a discrete age structure model to evaluate the effectiveness of different vaccines against adults to figure out the impact and the question of whether a booster vaccine is needed for adults. When establishing the mathematical model, the researchers divides the population into adults and children and also considered the differences in the efficiency of different vaccines for adults. The main reason why this article makes such division is to analyze the impact of herd community among adults on the spread of COVID-19 among children. This article divides the population into different age groups by adjusting the input of the model parameters, and more effectively explores the law of different vaccination coverage rates for herd immunity and reducing the probability of children being infected.

2.2 Agent model

2.2.1 Covasim model [5]. This paper introduced the principle of Covasim model, which is developed to support policy decision-making in COVID-19 fields for countries with different subnational settings. One core feature of Covasim is to simulate the effect of interventions on contagion outcomes. This model has been used by several countries including the US, the UK. For our project, we can use this model to simulate the contagion and can save a lot of time with its automatically producing reasonable parameters.

To achieve the simulation of intervention, we can either write our own intervention class derived from the basic intervention class or simply assign a function upon the model. And this model provides a built-in intervention class for vaccines which will be helpful to us. A strength of the model is that it has a high computational efficiency so we can run realistic scenarios on scales of tens of thousands of infections on our personal computers.

One shortcoming of this model is that currently calibration must be performed externally to the Covasim model with optimization libraries like sciPy.

2.2.2 Covasim implementation: large scale simulation [6]. This paper implements a simulation on Covasim model with the COVID-19 data from the US and compares it to the reality.

This paper provides a good example of how to create the initialization (setting characteristics of agents for t=0) and rules governing its update, thereby producing data for analysis on the Covasim model.

There are three main limitations within this simulation: (1) the number of vaccines that can be administered each month (2) biological aspects, and (3) healthy or asymptomatic carriers. (1) and (3) are problems our project may encounter too because the data of the amount of the administered vaccines and the amount of the asymptomatic carrier are out of reach in most countries and areas in the world. So we need to further figure out the method to estimate those data.

Besides, this paper only implements the simulation for the US, while the simulation results might be different in other areas which can help us with the justification for the vaccine simulations and further predictions.

2.3 COVID-19 vaccine

To reflect the effect of vaccines in our simulation, we need to know not only the number of vaccinated people but also the vaccine effectiveness against infection, symptomatic infection, and hospitalization. The report [1] gives a brief summary of current research and some key findings of the Pfizer-BioNTech COVID-19 vaccine are listed below:

- The effectiveness against infection decreases from 90% $\sim$ 100% to 42% $\sim$ 80% from February to July
- The effectiveness against symptomatic infection decreases from 87% $\sim$ 97% to 64% $\sim$ 66% after 200 days
- The effectiveness against hospitalization decreases from 84% $\sim$ 100% to 75% $\sim$ 95% from February to July

We are going to use a linear function to express the decline of vaccine effectiveness. Cause different research has shown different effectiveness decline speed, we will also change this parameter to find out how the decline speed affects the spread of COVID-19.

2.4 Policy response

The policy response of the government, such as travel restriction, gathering cancelation, mask requirement, also plays an important part in preventing the spread of COVID-19. To quantify the strictness of policy response, the research [3] evaluates the containment policies, closure policies and COVID-19 testing regime, and combines them as the 'Stringency index' of policy response, which is available at this Github repo. However, this data doesn't take the people's reaction towards the government policies into consideration. The Google Community Mobility Reports (Our World in Data transfers the reports into a dataset) shows the change of the movements of people, which may indicate how people respond to restriction policies.

We are going to use the 'Stringency index' as the quantified number of government policy response. We will also make necessary adjustments if an important policy change is not reflected in the index.

3 DATA SOURCE

3.1 Singapore MOH

The Ministry of Health of Singapore updates the daily COVID-19 situation on the official website. Unfortunately, the official website doesn't provide machine-readable format data. The dataset COVID-19 Singapore contains the information listed below from Jan 23rd, 2020 till now. Vaccination data from this dataset is partially lost (from Jan 11st, 2021 to June 30th, 2021). However, the dataset from Our World in Data provides this part of the data.

- Cumulative/Daily confirmed case number
- Cumulative/Daily hospitalized/isolated case number
- Cumulative/Daily discharged/death case number
- Cumulative/Daily one-dose/fully vaccinated individuals number

3.2 Taiwan CDC

The Centers for Disease Control of Taiwan also updates the daily COVID-19 situation on the official website. This Github repo contains the information listed below from Jan 21st, 2020 till now, whose data comes from this Google Spreadsheet (maintained by anonymous users of the PTT forum), Taiwan CDC official website, and NCHC dashboard.

- Cumulative/Daily confirmed case number (categorized by county)
- Cumulative/Daily hospitalized/isolated case number
- Cumulative/Daily discharged/death case number
- Cumulative/Daily one-dose/fully vaccinated individuals number

4 EXPECTED TIMELINE

- 6th Oct ~ 13th Oct: Data cleansing
- 14th Oct ~ 26th Oct: Mathematical model (parallel) implementation & Milestone report
- 27th Oct ~ 11th Nov: Agent model implementation based on Covasim; Mathematical model fine tunning; Final report
- 12th Nov ~ 15th Nov: Final presentation

Generally Zishu Liu and Jichuan Zhang will work on the mathematical model and Yuxin Xie will work on the agent model. We will work on the presentation and final report together.

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