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Modeling COVID-19 spreading — evidence from Canada

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Abstract. This study delves into the comprehensive examination of the COVID-19 pandemic that has been affecting the global community since late 2019. The repercussions have been ameliorated to some extent with the advent of effective vaccination campaigns, albeit the impact varies across regions and outbreaks. Beginning with an introduction to the fundamental epidemiological SIR (Susceptibility, Infection, Recovery) model, the research extrapolates it to reflect the complex dynamics of the COVID-19 scenario, employing data from Ontario, Canada, to ground the analysis in real-world observations. Several parameters and initial conditions inform the development of differential equations and ensuing line graphs within the scope of the extended VSEAIR (Vaccinated, Susceptible, Exposed, Asymptomatic Infected, Symptomatic Infected, and Recovered) model. The study scrutinizes the interplay of two pivotal aspects: the effectiveness of vaccination and the influence of governmental interventions. It offers a rigorous review of the trajectory of COVID-19 in Ontario, shedding light on potential strategies to optimize the response to the pandemic and contributing to evidence-based policymaking.

Keywords: COVID-19, SIR model, vaccination, VSEAIR model.

1. Introduction

This research extends previous investigations on the widely discussed topic of the ongoing COVID-19 pandemic [1, 2]. The primary focus is to understand the correlation between infection rates and two critical factors: vaccination and government policies regarding reopening. Throughout history, humanity has grappled with infectious diseases, from the Black Death to the current COVID-19 pandemic, owing to their transmissibility and potential fatality. Several elements, including the natural environment, population size, and public health measures, influence the onset and progression of infectious diseases, making them a central concern in epidemiology. Mathematical and statistical models, lauded for their quantitative precision and scientific rigor, have been long used to study the spread of viruses. In this study, we use the traditional SIR (Susceptible, Infected, and Recovered) epidemiological model as a foundation, exploring how the addition of crucial elements like vaccination and government interventions affect model outputs and simulation outcomes under various coefficient settings. The resultant findings help elucidate the roles vaccination and government regulations play in pandemic scenarios.

In March 2020, the World Health Organization (WHO) declared the COVID-19 outbreak as a global pandemic [3]. Shortly after, the premier of Ontario, Doug Ford, announced a state of emergency due to the escalating COVID-19 situation and implemented a series of containment measures, including the closure of public spaces and mandatory indoor mask-wearing. Currently, with concerns regarding the

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economy and mental health, the government has decided to reopen all businesses and lift the indoor mask mandate. In light of these developments, we have expanded the traditional model to include three additional components that reflect current circumstances: E (Exposed), A (Asymptomatic), and V (Vaccinated). Using these five quantities, we construct a novel model called the VSEAIR (Vaccinated, Susceptible, Exposed, Asymptomatic Infected, Symptomatic Infected, and Recovered) model [4], and further analyze its results to provide insights and recommendations.

2. Modelling

This research employs a dynamic epidemiological model. Commonly, the Susceptible-Infectious-Removed (SIR) model is employed for epidemiological studies, providing basic insights into the transmission dynamics of infectious diseases [5]. Nevertheless, the complexity of these diseases often defies expression in a simple function set, rendering the SIR model too simplistic. Consequently, we expanded this model by introducing an 'Exposed' (E) category, culminating in the Susceptible-Exposed-Asymptomatic-Infectious-Recovered (SEAIR) model to capture the dynamics of the COVID-19 epidemic more accurately. We've assumed that the epidemic is short-lived, and therefore, other factors are not considered. As for the total population size, it remains unchanged throughout the epidemic's duration.

Our model assumes that individuals removed from the disease cannot be infected again, and vaccination during the exposed period does not offer any protection. Ultimately, all those exposed or infected will be removed from the susceptible population. We also presuppose a 100% positive conversion rate, implying that non-infectious infected individuals will inevitably transition to either symptomatic or asymptomatic infected statuses.

In this context, the dependent variables are Susceptible (S), Exposed (E), Infectious (I), and Recovered or Deceased (R), while time (t), measured in days, is the independent variable. As the model focuses on a short time frame, births and immigration (μ) are not considered, thereby classifying it as an endemic SEAIR model.

In our model, we categorize the population into several groups: Susceptible (S=S(t)), the unvaccinated individuals susceptible to infection; Exposed (E=E(t)), those infected but not yet infectious; Infectious (I=I(t)), individuals who are symptomatic; Asymptomatic (A=A(t)), those infected but not symptomatic; Removed (R=R(t)), individuals no longer capable of transmitting the disease, including both recovered and deceased individuals; and Vaccinated (V=V(t)), the fully vaccinated individuals.

We consider three scenarios: without vaccination, with vaccination, and with government restrictions. By comparing the unvaccinated scenario with the vaccinated and government-regulated scenarios, we aim to track the progression of the COVID-19 situation under each circumstance. We anticipate that both vaccination and government regulation play a significant role in controlling the pandemic, underlining the importance of these interventions.

Susceptible denotes as $S = S(t)$, represents the number of people who could potentially become infected and have not yet been vaccinated;

Exposed denotes as $E = E(t)$, refers to the number of people who have been infected but are not yet infectious;

Infection denotes as $I = I(t)$, corresponds to the number of people who are currently symptomatic due to the infection;

Asymptomatic denotes as $A = A(t)$, signifies the count of infected individuals who are not exhibiting any symptoms;

Removed denoted as $R = R(t)$, represents the number of people who are no longer capable of transmitting the disease. This category includes individuals who have successfully recovered from the infection as well as those who have unfortunately succumbed to it;

Vaccinated denoted as $V = V(t)$, indicates the number of people who have received full vaccination against the disease.

β_S: Contact transmission rate from symptomatic infected individuals.

β_A: Contact transmission rate from asymptomatic infected individuals.

α_1: The fractional positive constant lies between 0 and 1;
α_2: The fractional positive constant lies between 0 and 1, and $\alpha_2 = 1 - \alpha_1$;
γ_1: Recovered rate from asymptomatic infected individuals.
γ_2: Recovered rate from symptomatic individuals.
d: Death rate;
μ: Birth and immigration rate
θ: Growth in transmission due to reopen policy Step 2
Ω: Growth in transmission due to reopen policy Step 3
v: Which is the rate of individuals who are fully vaccine
The differential equation for general SEIR Model without vaccinated:

$$\frac{dS}{dt} = \mu N - \frac{\beta S(t)I(t)}{N} - \mu S(t) \tag{1}$$

$$\frac{dE}{dt} = \frac{\beta S(t)I(t)}{N} - (\mu + \alpha)E(t) \tag{2}$$

$$\frac{dI}{dt} = \alpha E(t) - (\gamma + \mu + d)I(t) \tag{3}$$

$$\frac{dR}{dt} = \gamma I(t) - \mu R(t) \tag{4}$$

Because we just focus on the spreading in a short-term, so that we do not consider the births and immigration ($\mu = 0$). And use I(t) and A(t) instead of single I(t).

Then we get this for the new form:

$$\frac{dS}{dt} = -(1+\theta)(1+\Omega)\left(\frac{\beta_S S(t)I(t)}{N} + \frac{\beta_A S(t)A(t)}{N}\right) - vS \tag{5}$$

$$\frac{dE}{dt} = \left(\frac{\beta_S S(t)I(t)}{N} + \frac{\beta_A S(t)A(t)}{N}\right)(1+\theta)(1+\Omega) - [\alpha_1 + \alpha_2]E(t) \tag{6}$$

$$\frac{dI}{dt} = \alpha_1 E(t) - \gamma_1 I(t) \tag{7}$$

$$\frac{dA}{dt} = \alpha_2 E(t) - \gamma_2 A(t) \tag{8}$$

$$\frac{dR}{dt} = \gamma_1 I(t) + \gamma_2 A(t) \tag{9}$$

$$\frac{dV}{dt} = vS \tag{10}$$

In our model, we have made the simplifying assumption that birth and death rates are negligible within the population under consideration. By doing so, we are able to establish that the total number of individuals across all states (Susceptible, Exposed, Infectious, Asymptomatic, Recovered, and Vaccinated) remains constant throughout the duration of our study.

$$S(t) + E(t) + A(t) + I(t) + R(t) + V(t) = 0 \tag{11}$$

Initial condition with:

$$S(0) = S_0 > 0;\ E(0) = E_0 > 0;\ I(0), A(0) = I_0, A_0 > 0;\ R(0) = R_0 = 0 \tag{12}$$

It illustrates that susceptible(S) has a opposite trend to Infected(I).

3. Model with vaccinated

From this part, we will consider about our model with adding the variable of vaccinated. To make our model more certain, we consider the effectiveness of the vaccine is a fix value. That is, 60% of the

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infection prevention efficiency, due to the current omicron mutant viruses raging. We emphasize that in our model we consider the three shots vaccinated population as fully vaccinated in our model.

For this new model, all the coefficients' values and initial values are same to the pervious 'no vaccinated model' in order to make comparation. However, we will fill values into parameters about vaccinated in this 'with vaccinated model'. The fully vaccinated rate v is 48% in Ontario so far. Those who are fully vaccinated are still at risk of contracting the virus (Omicron) since the efficiency of the vaccine due to Omicron [6, 7]. The data shows that the effective rate of fully vaccinated for omicron is 0.6. We know that about 40% public is fully vaccinated but not immune in Ontario. Thus, when we indicate the initial value for V0 is the total population multiply the fully vaccinated rate multiply the actual effective rate. Then we conduct our V0 is 2850000.

As for our model with vaccinated group, we will collect new data corresponding to vaccinated group. At this point, the situation is quite different than the previous no vaccinated situation. Indeed, we will use the data from Ontario, Canada as comparison. We choose data for the most recent date, as of the end of March 2022 [6]. For this model including vaccinated, we will see how the variable of V will affect the entire model. In this way, we can know to what extent the vaccinated group will affect COVID-19 and its significance. After entering all the values into the model and run the code. We have this graph below.

3.1. Policy 1: $\theta = 0$ and $\Omega = 0$

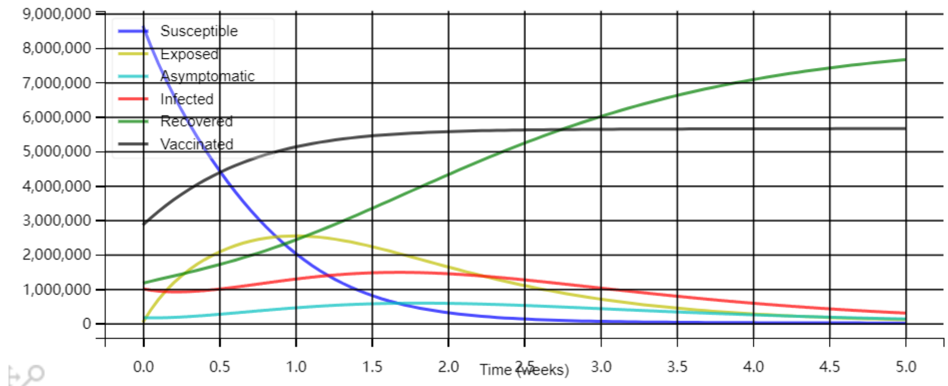

Figure 1. The SEAIRV mode with vaccination in 5 weeks.

From Figure 1, we could clearly see that the numbers of exposed, infected and asymptomatic group of people are an uptrend in early period. When time goes, they will come down slowly due to the rise of vaccinated group of people. While the number of recovered people always has a trend that goes up. This shows the situation of this pandemic COVID-19 becomes better.

3.2. Policy 1 and no vaccination

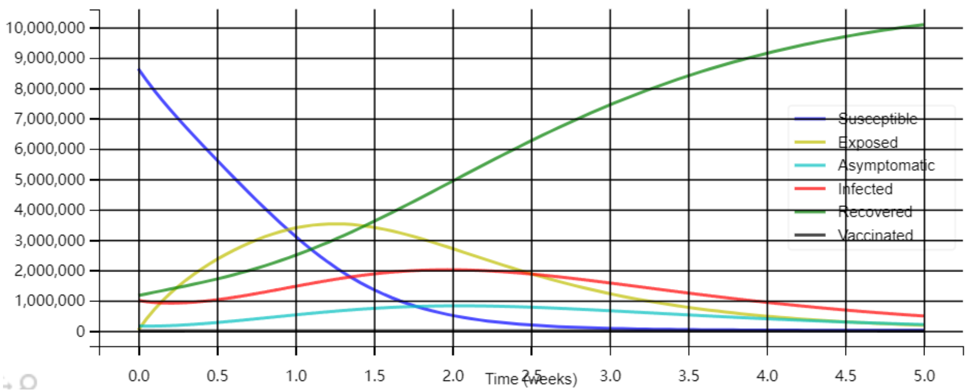

Figure 2. The SEAIRV mode without vaccination in 5 weeks.

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If we compare the model without vaccinated with the model with the vaccinated, that will be clearer. Figure 2 above is the model without vaccinated. We know that as time goes by, the population of exposed, infected, and asymptomatic groups will decrease while the recovery group increase. In this case, the susceptible group decrease because of the increase of recovery group. In these two graphs, their overall trend is similar. However, the curve line of groups of exposed, infected, and asymptomatic in vaccinated model is flatter than that in non-vaccinated model [8]. Besides, their peak points are different, in which vaccinated model is lower than non-vaccinated model. Furthermore, the line of susceptible group declines greater in vaccinated model than that in non-vaccinated model. In other word, the situation of COVID-19 will come better faster after adding the variable of vaccinated [9].

In conclusion, taking vaccine is very useful to control COVID-19, there is a large decline of exposed, infected, and asymptomatic population. This is also in line with the assumptions we mentioned earlier. Taking vaccine has a significant positive effect on COVID-19. All in all, developing vaccines is one of the best ways to fight against communicable diseases. Human should develop on vaccines to fight possible pandemic in the future.

4. Model with government regulation

Apart from vaccination, non-pharmaceutical strategies have also significantly contributed to pandemic management. We direct our attention in this section towards the relationship between disease incidence and the reopening regulations implemented by the Ontario government [10]. To simulate the impact of reopening policies on the virus's transmission rate, we've included parameters θ and Ω in our model. The specifics of the reopening policy are as follows:

Step One: Initial emphasis on recommencing outdoor activities involving smaller groups, where transmission risk is lower, along with controlled resumption of retail activities.

Step Two: Further extension of outdoor activities and limited restart of indoor services with small groups of people adhering to mask-wearing guidelines.

Step Three: Broadened access to indoor environments, albeit with restrictions, including scenarios where larger groups are present and mask-wearing may not be consistently possible.

We have considered Step One as a complete isolation situation to render our model more realistic. The parameters θ and Ω represent the increase in transmission due to reopening policies in Steps Two and Three, respectively. In this paper, we consider Step One as a full isolation situation to make our model more realistic. Parameters θ and Ω represent the growth in transmission due to reopen policy Step Two and Step Three respectively. We set $\theta = 0.25$ and $\Omega = 0.2$ is our original assumption. And the graphs below show the result from the simulation [1].

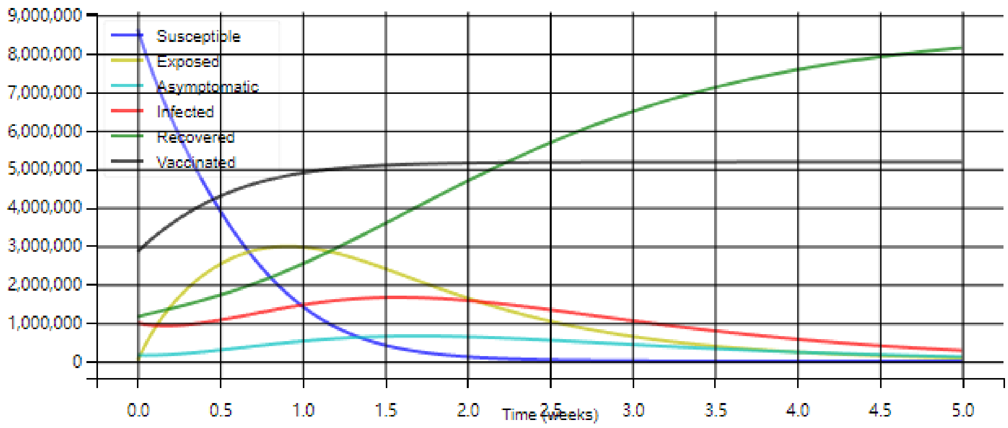

Figure 3. The SEAIRV mode with vaccination and government regulation in 5 weeks (policy Step 2: $\theta = 0.25$ and $\Omega = 0$).

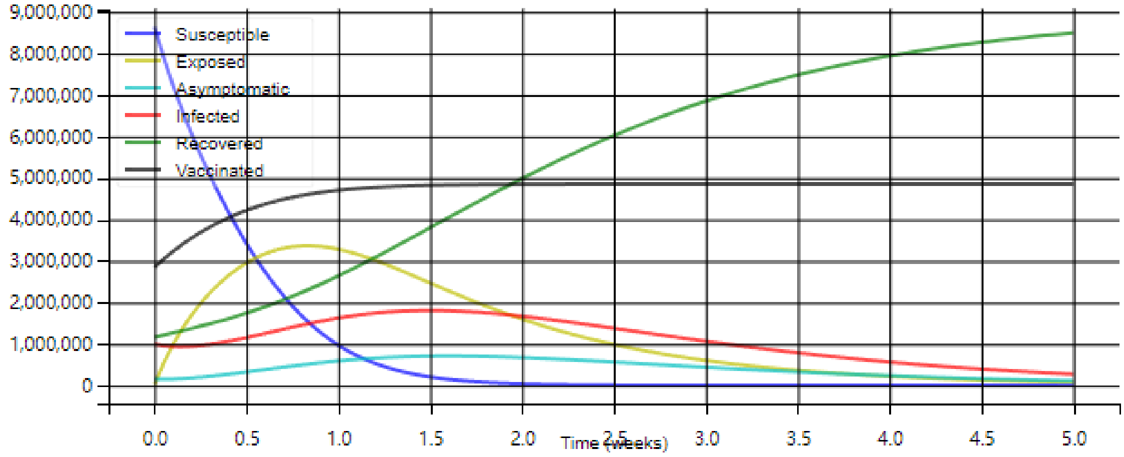

Figure 4. The SEAIRV mode with vaccination and without government regulation in 5 weeks (policy Step 3: θ = 0.25 and Ω = 0.2).

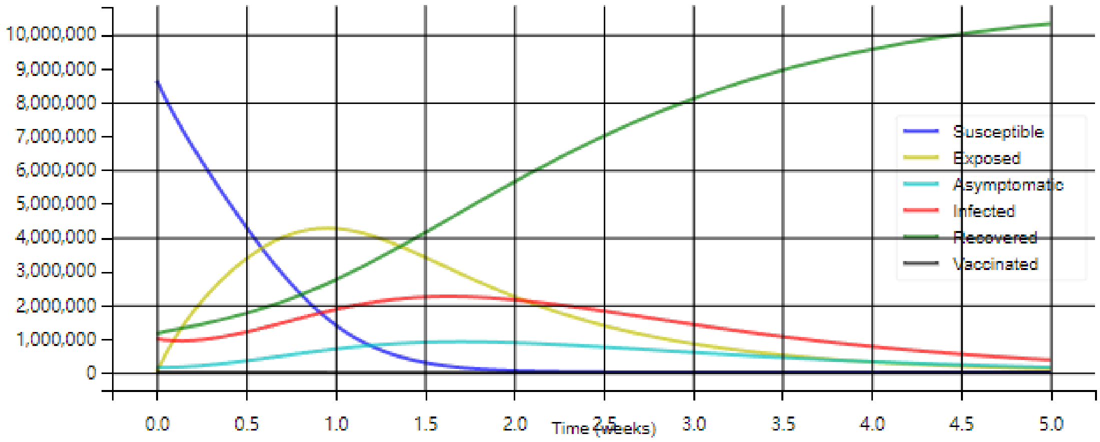

Figure 5. The SEAIRV mode without vaccination and government regulation in 5 weeks (policy Step 3 and no vaccination).

Now we can draw conclusions from a series of comparisons. Firstly, through the comparison of Figure 1, Figure 3 and Figure 4, The number of exposed, symptomatic infected asymptomatic infected, and recovered grows up with the increasing openness through policy change from Step1 to Step 2 and Step 2 to Step 3. Meanwhile, the decreasing speed of the number of susceptible has become faster during the policy change. Clearly, the particular reason for this circumstance is that with the growth of openness, more people get exposed to the Omicron virus and become potentially infected [9, 10]. And the increase in the number of exposed leads to a faster reduction of susceptible. On one hand, the increase in the number of infections is a negative impact of reopen policy. On the other hand, the faster reduction of the number of susceptible demonstrates that the end of the entire pandemic might come earlier.

Secondly, through the comparison of Figures 4-5, the result is intuitive:

From Figures 4-5, the peak number of exposed increases by nearly 0.9 million; peak number of symptomatic infected and asymptomatic infected increases by nearly 0.44 million and 0.19 million.

To sum up everything that has been stated so far, the reopen policy will come at a heavy price as an increase in infection. However, it can also basically end the pandemic with herd immunity. With the help of vaccinations, reopening policies can be implemented smoothly with less incidence [11].

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5. Conclusion

In this research, we have proposed a COVID-19 model that integrates vaccination initiatives and government regulations. Relative to the conventional SIR model, our approach is more precise and holistic. The core objective of this model is to examine the relationship between infection rates and vaccination efforts as well as government reopening policies.

In summary, based on the simulations conducted, it is clear that vaccination plays a crucial role in decreasing the incidence of COVID-19, displaying a negative correlation with infection rates. Conversely, government reopening policies show a positive correlation with disease incidence; as the level of openness expands, so does the rate of infection. It's possible that reopening policies might cause a temporary surge in infection rates. Nonetheless, these same policies can potentially contribute to the end of the pandemic through the establishment of herd immunity.

The implementation of reopening policies can be substantially enhanced with the aid of vaccination efforts. When supported by an effective vaccination campaign, reopening policies might be executed more seamlessly and cost-effectively.

Nevertheless, it's crucial to note that the timing and extent of these reopening strategies must be thoughtfully and carefully considered. In real-world scenarios, data isn't merely a collection of numbers - it represents the lives and well-being of individuals. Hence, any decisions made based on this data should prioritize the safety and health of the population.

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