A model to quantify the efficacy of COVID-19 related policy measures

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I. Abstract

The Covid-19 pandemic has wreaked havoc around the world, leading to millions of deaths and overwhelmed healthcare facilities. It has led to several public policy decisions like social distancing, mask mandates and vaccination. Here we extend the canonical differential equation–based SIR model [1] to a version named SEIR-V which captures the complexities specific to Covid-19, including the presence of both symptomatic and asymptomatic infected individuals as well as a socially distanced and vaccinated sub-population. Simulations of the SEIR-V model predict that a combination of early vaccination and social distancing nearly halves the mortality rate due to Covid-19 and protects a majority of the population from acquiring the infection (compared to the no restrictions/ no vaccination case). This shows that the SEIR-V model can serve as a mathematical basis behind the public policy decisions implemented to curb the spread of the pandemic.

II. Methods

The transition between each compartment of the SEIR-V model (Fig. 1) is represented by Ordinary Differential Equations (ODEs). The ODEs have been numerically solved to obtain their dynamics over time in order to understand the effect of parameters like social distancing (which reduces the infection transmission rate) and vaccination (with a rate labeled by *k*) on the spread of the virus in a population.

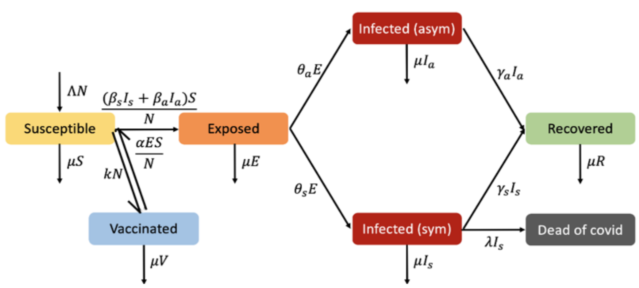

Figure 1. Flow Diagram of SEIR-V (Susceptible, Exposed, Infected, Recovered, Vaccinated) model

There are 7 ODEs used to represent the transitions between the 7 compartments in the model, and the contribution of each parameter (positive or negative) is given by whether the arrows point into or out of the compartment respectively. The ODEs are as follows: *

$$\frac{dS}{dt} = \Lambda N - \mu S - \frac{\alpha ES}{N} - \frac{(\beta_s I_s + \beta_a I_a)S}{N} - kN \tag{1}$$

$$\frac{dE}{dt} = \frac{\alpha ES}{N} + \frac{(\beta_s I_s + \beta_a I_a)S}{N} - \mu E - (\theta_a + \theta_s)E \tag{2}$$

$$\frac{dI_a}{dt} = \theta_a E - \mu I_a - \gamma_a I_a \tag{3}$$

$$\frac{dI_s}{dt} = \theta_s E - \mu I_s - \gamma_s I_s - \lambda I_s \tag{4}$$

$$\frac{dR}{dt} = \gamma_a I_a + \gamma_s I_s - \mu R \tag{5}$$

$$\frac{dD}{dt} = \lambda I_s \tag{6}$$

$$\frac{dV}{dt} = kN \tag{7}$$

The parameters used for the ODEs in the model, along with their estimated values [2], are given in the Table I.

TABLE I. TABLE OF ESTIMATED PARAMETERS (UNITS OF DAY^{-1})

Serial No.	SEIR-V model		
	Parameter description	***Value without social distancing***	***Value with social distancing***
1	Natural birth rate (Λ)	3.18 x 10^{-5}	3.18 x 10^{-5}
2	Natural death rate (μ)	2.11 x 10^{-5}	2.11 x 10^{-5}
3	Break-through cases (α)	0.05	0.03
4	Exposure rate (β)	0.3	0.16
5	Infection transmission rate (θ)	0.06	0.03
6	Recovery rate (γ)	0.05	0.07

The *odeint* package in Python has been used to numerically integrate and plot the dynamics of these ODEs (on a test population of N=10,000 people).

III. Simulation Results

When simulated under four different policy actions (no action, only social distancing, only vaccinations and a combination of both), the dynamics of Covid-19 spread are obtained as follows. To make the effects of each policy action more visible, the curve for the Total infected population in Figs. 2-6 aggregates the *Exposed*, *Symptomatic Infected* and *Asymptomatic Infected* compartment numbers.

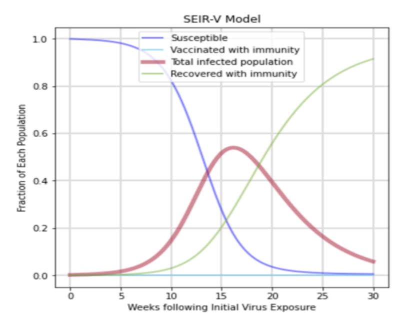

Figure 2. No Action (Death rate: 2.31% ; Uninfected population: 0.5%)

We see that without any policy measures to combat the pandemic (Fig. 2), almost the entire population gets infected and the mortality is very high(>2%).

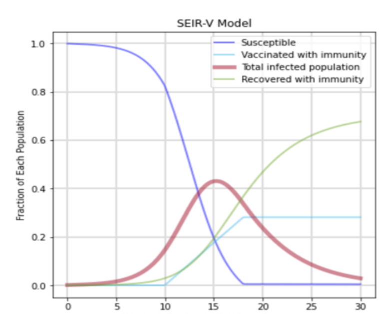

Figure 3. Delayed Vaccination with k = 0.005 day^{-1} (Death rate: 1.71% ; Uninfected: 28.57%)

* Variable definitions can be found in APPENDIX I at the end

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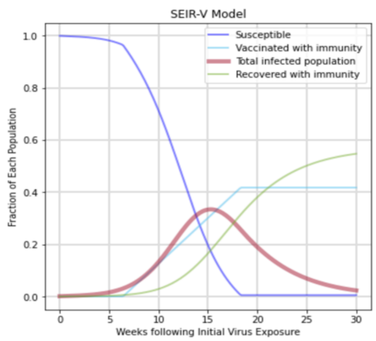

Figure 4. Rapid Vaccination with k = 0.01 day^{-1} (Death rate: 1.39% ; Uninfected: 42.23%)

Introducing vaccinations (Figs. 3 and 4) drastically decreases the death rate and the spread of infection. A rapid vaccination rollout further increases protection and almost halves the death rate (Fig. 4).

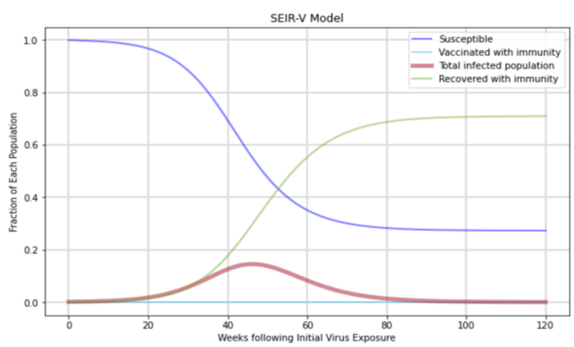

Figure 5. Social Distancing (Death rate: 1.80% ; Uninfected: 24.33%)

In case there are no vaccination drives, social distancing alone decreases the spread of the infection (Fig. 5). It induces a flattening of the *Infected* curve (distributing the spread of Covid-19 over a longer time period), and makes the patient inflow manageable for the limited hospital resources available.

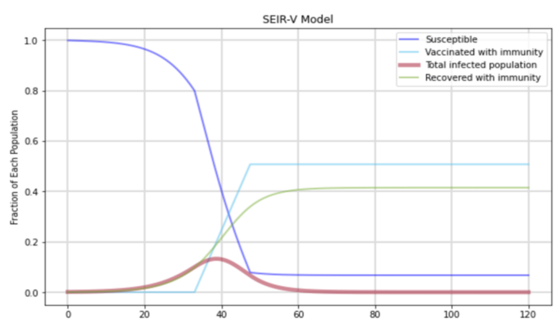

Figure 6. Social Distancing and Vaccination (Death rate: 1.05% ; Uninfected: 57.46%)

Finally, combining social distancing with a rapid vaccination response (as shown in Fig. 6) significantly increases the fraction of uninfected individuals to over half the population and reduces the death rate to just 1%. A summary of the predicted infection and mortality rates is given in Table II.

TABLE II. SUMMARY TABLE

Serial No.	**Conditions and Effects**		
	Simulation Conditions	***Death rate***	***Uninfected Population***
1	No Action	2.31 %	0.50 %
2	Delayed Vaccination	1.71 %	28.57 %
3	Rapid Vaccination	1.39 %	42.23 %
4	Social Distancing	1.80 %	24.33 %
5	Social Distancing and Vaccination	1.05 %	57.46 %

IV. DISCUSSION

Although this paper simulates the COVID-19 outbreak in a small test population of 10,000 people, the results show the general significance of timely vaccination and social distancing in curbing the spread of infection. The SEIR-V model created to model Covid-19 dynamics in this paper is realistic because it estimates the mortality rate to values that fall within the range of the rates published by WHO during the course of the pandemic for India [3]. This shows that it can capture the general trends of the Covid-19 transmission dynamics as well as the effectiveness of public policy decisions instituted during the pandemic. Therefore, the framework of the SEIR-V model (with more optimized parameters) may be an important consideration while building more complex models in the future to predict the outbreak of Covid-19 and similar pandemics.

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[3] Our World in Data, *Mortality Risk of Covid-19*, 2021, https://ourworldindata.org/mortality-risk-covid (last accessed: Oct 4, 2021)

APPENDIX I (VARIABLE DESCRIPTION)

N : the total population
S : the susceptible population
E : the exposed population
I_a : the infected, asymptomatic population
I_s : the infected, symptomatic population
R : the recovered population
D : the deaths in the population
V : the vaccinated population
Λ : the birth rate
μ : the death rate
α : the break–through case rate
β_a : transmission rate when social distance obeyed
β_s : transmission rate when social distance not obeyed
θ_a : the rate of infection for asymptomatic population
θ_s : the rate of infection for symptomatic population
γ_a : the recovery rate for asymptomatic population
γ_s : the recovery rate for symptomatic population
λ : the death rate due to Covid-19
k : the recovery rate