EpiPolicy

A tool for combating epidemics

COVID-19 brought along an increasing demand for research toward combating epidemics. A group at New York University Abu Dhabi developed a tool, EpiPolicy, to explore and visualize the effects and costs of intervention plans.

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In many parts of the world, the COVID-19 pandemic has cost lives as well as economic hardship. It has included disruptive and costly interventions such as border closures, social distancing, and remote education. Each intervention has both benefits and costs, considering their respective social and economic burdens. For example, border closures can be effective at the start of an outbreak as they provide enough time for other less costly interventions to be implemented—such as enforcing mask mandates, which require time for both mask production and distribution. This paper presents EpiPolicy,[1] a tool that enables users to simulate an epidemic along with mitigating interventions. This tool may facilitate policymakers in making evidence-based decisions for how to combat an epidemic.

In this article, we will describe the motivations and inner workings of EpiPolicy's simulator to illustrate how one can conduct multiple what-if analyses to determine a cost-effective schedule of interventions.

BASICS OF EPIDEMIC MODELING

When it comes to modeling the spread of disease, compartmental models, such as the SIR (Susceptible, Infectious, and Recovered) model, have been widely used to predict epidemic consequences such as how fast a disease spreads and how long the outbreak may last.[2]

In Figure 2, we illustrate a complex compartmental model for COVID-19 with 15 compartments. It captures specific disease features based on transition rates. For example, the incubation period can be derived from the transition rates from exposed to infected. The model describes how individuals transition through the different stages of disease through compartments for exposed, asymptomatic, pre-symptomatic, mild infection, severe infection, critical infection, and recovered individuals. It allows for reinfection by a transition edge from the recovered compartment back to the susceptible compartment. Epidemiologists can customize the parameters of this EpiPolicy model for different groups in the population, such as children, adults, and seniors. For example, we can model an epidemic in which seniors

1 http://epipolicy.github.io

2 https://bit.ly/epipolicy

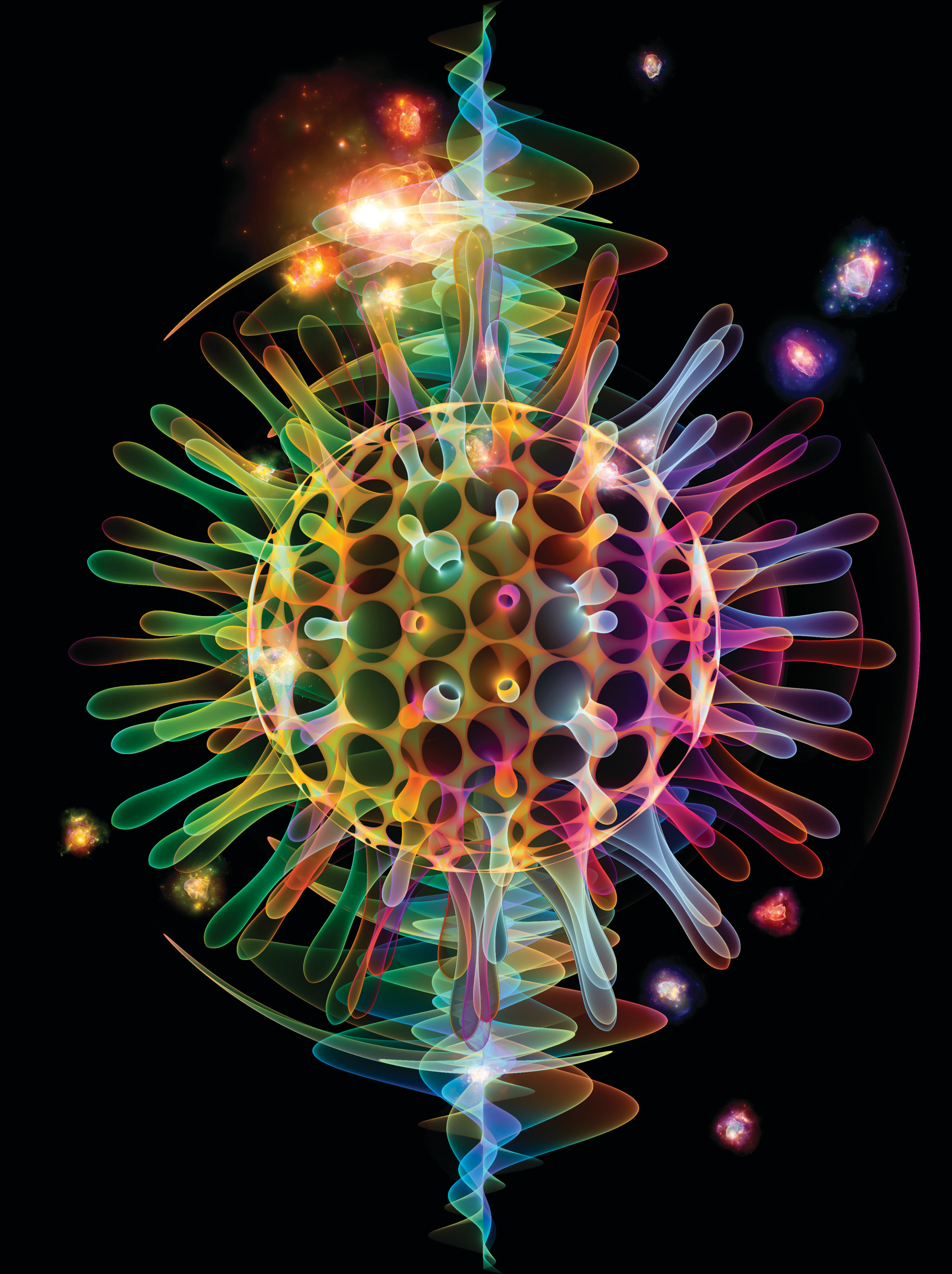
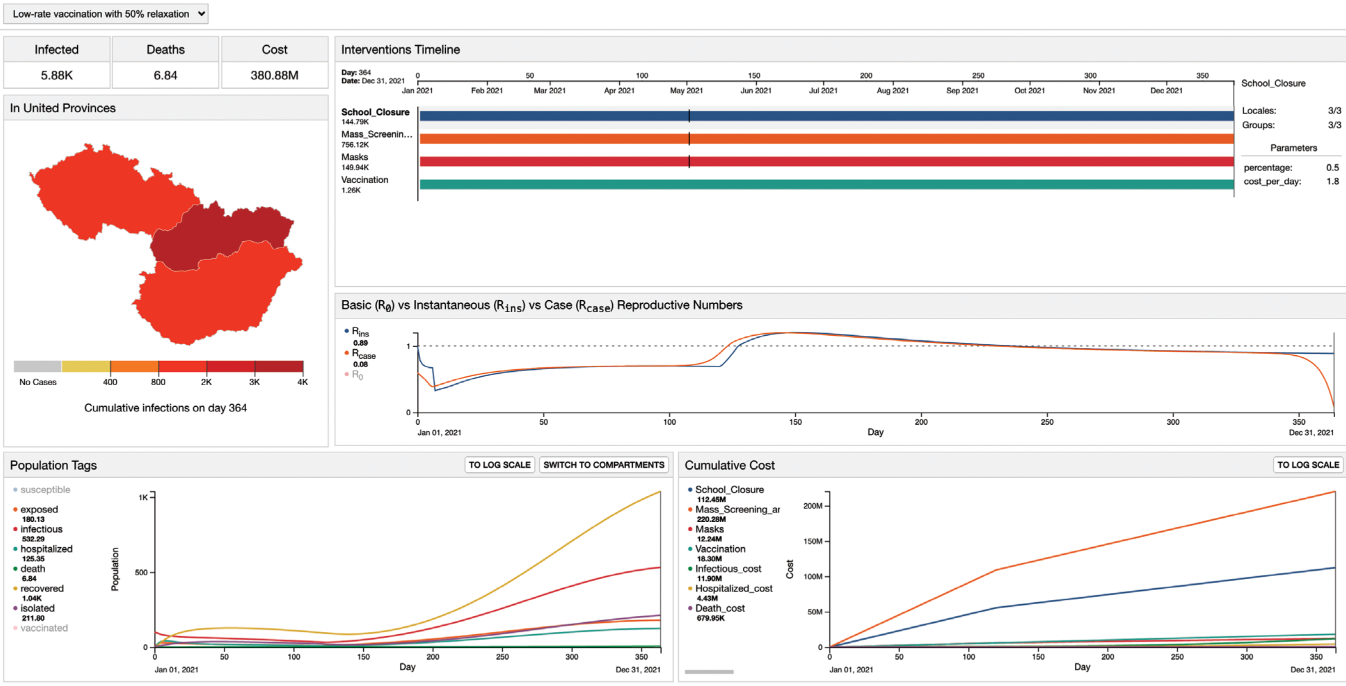


Figure 1. EpiPolicy provides a visual dashboard to explore the effects and costs of an intervention plan on the different administrative locales in the fictitious country of the United Provinces. Here, we see a plan with four interventions: school closures, mass screening with contact tracing, mask-wearing mandates, and vaccinations. In the first four months of the schedule, all non-pharmaceutical interventions are applied with high intensity and then relaxed for the following eight months. Vaccinations are administered throughout the year.



have a higher likelihood of developing severe and critical complications.

Depending on the interventions and policies under consideration, the disease model may contain more or fewer compartments. For example, in Figure 2, the hospitalization compartments H_{mild}, H_{sev}, and H_{cr} allow the modeling of outbreak scenarios where hospital capacities are exceeded and the design of interventions that increase hospital capacities. The quarantine compartments Q_s, Q_E, Q_{pre}, and Q_{asym} enable the design of interventions such as mass screening, contact-tracing, and isolation that detect suspected cases thus reducing the overall disease spread in the population by exposed, pre-symptomatic, or asymptomatic individuals.

EpiPolicy allows intervention developers to surface its control parameters to allow users to easily adjust the intensity or behavior of an intervention.

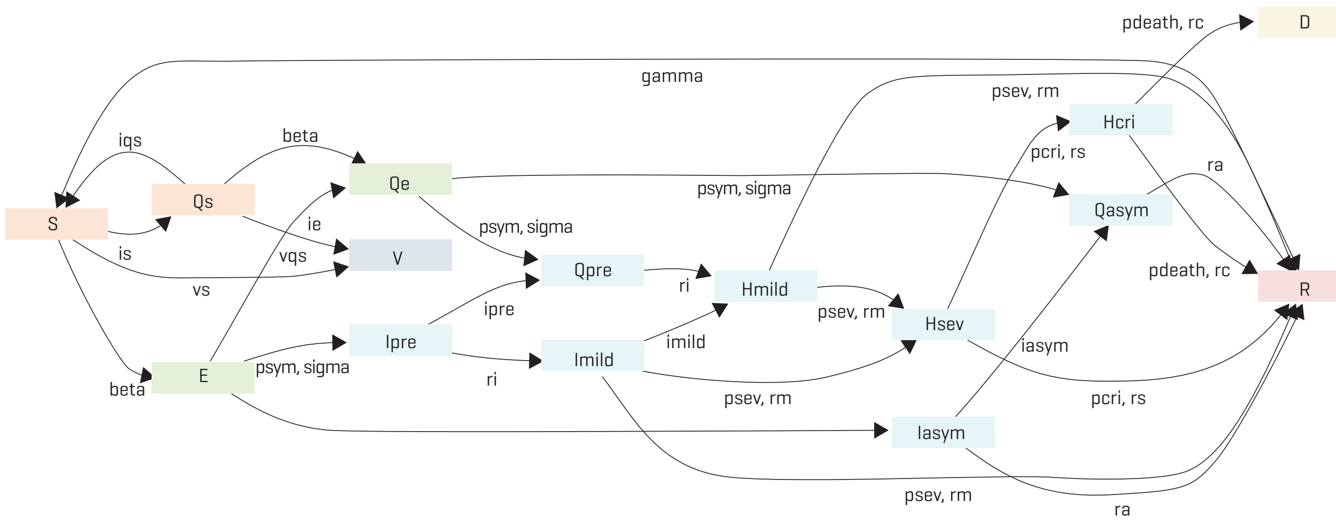
The model is based on a simplistic assumption: Vaccinated individuals are 100% immune to the disease. One can model partial immunity in vaccinated individuals by introducing a transition edge from the vaccinated compartment to the exposed compartment. All models, however, are approximations of reality. It is up to the disease modeling team to design a model that best reflects their current understanding of the disease, vaccinations, and interventions as well as to correctly parameterize it.

MOTIVATION

As a model grows in complexity, the number of parameters will increase. More data is needed to fit the parameters such as the recovery rate and mortality rate. Therefore, simulating a disease like COVID-19 and the effects of different interventions often requires a joint team of epidemiologists, computational modelers, data scientists, health economists, and public health officials. The process begins when such a team constructs a reasonably predictive disease model representative of their region of interest as a function of its unique socioeconomic and demographic characteristics. As the team considers possible interventions—such as school closures, social distancing, vaccination drives, etc.—they need to simultaneously model each intervention's effect on disease spread and economic cost. The team then engages in an extensive what-if analysis process to determine a cost-effective policy: a schedule of when, where and how extensively each intervention should be applied. This policymaking process is often an iterative and laborious programming-intensive effort where parameters are introduced and refined, model and intervention behaviors are modified, and schedules changed.

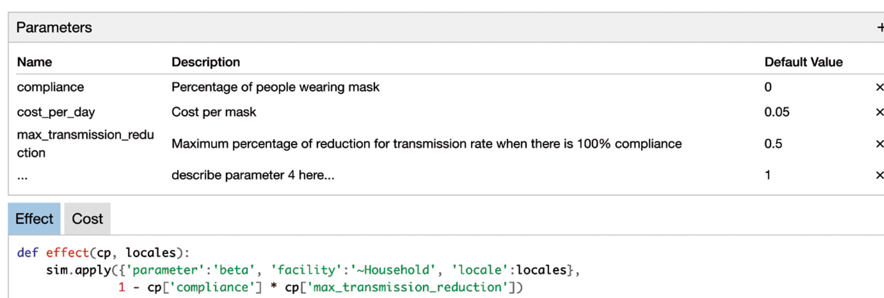
With EpiPolicy, this process is streamlined into well-defined steps, each handled by a separate UI page

Figure 2. A COVID-19 compartmental model with 15 compartments that accounts for different stages of COVID-19 symptoms as well as vaccination (V), quarantine (Qs, QE, Qpre, Qasym), and hospitalization (Hmild, Hsev, Hcri).



that provides clear and well-defined functionality, allowing users with different skill sets to effectively collaborate and explore different epidemic handling scenarios. For example, users with computational modeling experience can programmatically describe the behavior of interventions with respect to manipulating the disease models, while policymaking public health officials without programming experience can modify and explore intervention schedules easily by stating when, where, and how intensely different interventions are applied. You can learn more about our tool at epipolicy.github.io.

Figure 3. EpiPolicy surfaces the control parameters of the mask-wearing intervention. The effect method has two control parameters: compliance and maximum reduction in transmission rate. The cost method (not shown in the figure) has one control parameter: the cost per mask per day.



Parameters +

Name	Description	Default Value	
compliance	Percentage of people wearing mask	0	×
cost_per_day	Cost per mask	0.05	×
max_transmission_reduction	Maximum percentage of reduction for transmission rate when there is 100% compliance	0.5	×
...	describe parameter 4 here...	1	×

Effect Cost

```
def effect(cp, locales):
    sim.apply({'parameter':'beta', 'facility':'~Household', 'locale':locales},
              1 - cp['compliance'] * cp['max_transmission_reduction'])
```

ABSTRACTIONS AND INTERVENTIONS

In EpiPolicy, we model the spread of disease through interactions between groups of individuals (e.g. children or vulnerable sub-populations, such as seniors) within facilities (e.g. schools, workplaces, or malls) spread out across geographic and administrative locales (e.g. countries, cities, or districts). Mobility matrices describe the proportion of time individuals of one locale spend in another. For each facility, one can describe the proportion of time each group interacts with another group (e.g. children spend 90% of their time interacting with other children within a school). These three abstractions—groups, facilities, and locales—allow the specification of different kinds of interventions.

For example, a border closure intervention reduces the mobility between two locales by a certain rate. Groups allow the simulation of group-specific interventions such as shelter-at-home for vulnerable sub-populations. Within facilities, interventions like workplace capacity limits reduce the amount of time spent by certain groups in workplaces and the degree of interaction with other groups.

In EpiPolicy, each intervention is described by two python methods: effect and cost. An effect method usually modifies model parameters, population, or mobility characteristics such as transmission rate or time spent by individuals from one locale in another. A cost method estimates the dollar cost of the social or financial burden of an intervention. EpiPolicy allows intervention developers to surface its control parameters to allow users to easily adjust the intensity or behavior of an intervention. For example, one can surface the number of available vaccine doses per day or a vaccine's efficacy in a vaccination intervention. This allows users to quickly and easily increase or decrease the rate of vaccine administration or refine its efficacy based on evolving observational data. In Figure 3, we illustrate the effect method of a mask-wearing intervention. Here, we surface two control parameters for the effect method: compliance and the reduction in transmission rate due to wearing masks. At 100% compliance, the mask-wearing intervention reduces transmission by

Figure 4. The effect in terms of total number of infections, deaths, and dollar cost of relaxing the intensity of non-pharmaceutical interventions for two vaccination drives: a fast-rate one that vaccinates at most 4,500 adults and seniors a day and slow-rate one that vaccinates at most 1,250 adults and seniors a day.

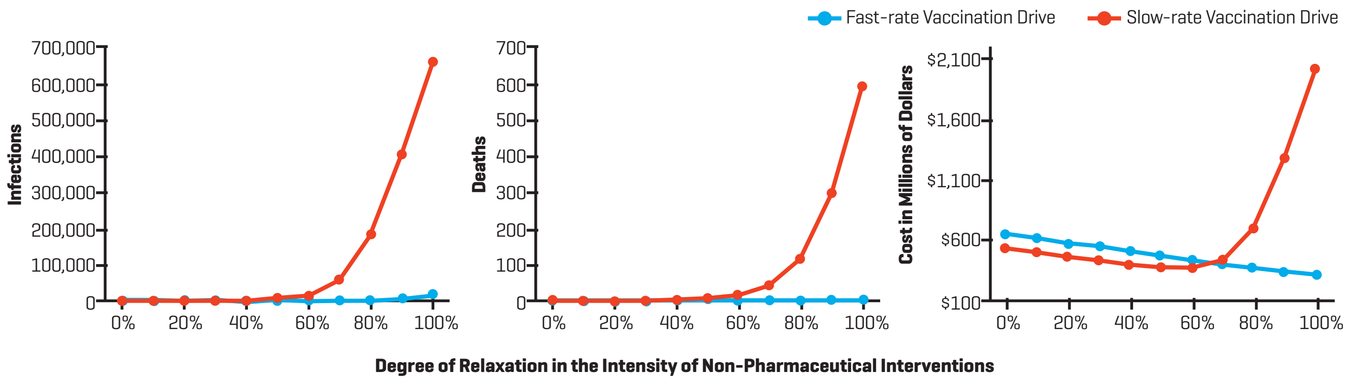


Table 1. Running costs for each intervention.

Interventions	Cost
School closure	$1.8 per affected person per day
Mass screening and contact tracing	$1.8 per affected person per day
Mask-wearing mandate	$0.05 per person per day
Vaccination	$40 per fully vaccinated person

Table 2. Dollar costs estimates for infections, hospitalizations, and fatalities.

Disease burden	Cost
Infections	$173 per infectious person per day
Hospitalizations	$250 per hospitalized person per day
Fatalities	$100,000 for each fatality

Table 3. The total infections, deaths, and economic cost at the end of a one-year simulation for the what-if scenarios under consideration by United Provinces officials.

Vaccination Drive	Relaxation Degree	Total Infections	Total Deaths	Total cost
Slow-rate	100%	659,938	591	$2,021,293,606
Fast-rate	100%	12,160	2	$326,601,453
Slow-rate	50%	5,818	7	$380,876,861
Fast-rate	50%	419	2	$479,086,269

50%. The net effect of wearing masks is of course controlled by the degree of compliance by the population. Policymakers can control how much compliance they anticipate from their community or expect to enforce.

It is often straightforward to construct interventions that operate independently, but how would one quantify the reduction in transmission rate when there are multiple interventions such as social distancing, mask enforcement, or school closure in place?

In EpiPolicy, we simulate the effect of an intervention either "directly" or "indirectly." Consider, for example, the transmission rate parameter. Direct-effect interventions, such as social distancing or mask enforcement, each reduce the transmission rate multiplicatively by a certain percent. To combine several such effects, we simply aggregate the effects of their multiplicative factors. Let's say social distancing and mask enforcement can each reduce the transmission rate by 20% and 60% respectively. Then the net reduction in transmission if the interventions were applied simultaneously would be: 1-(1-0.2)*(1-0.6)=0.68 or 68% reduction. Indirect-effect interventions, such as border closure or school closure, reduce the portion of time that individuals spend in transmission-prone locations. In the end, the effective transmission rate is a combination of the direct and indirect effect of these interventions.

EPIPOLICY IN ACTION

Let's see how a team of public health officials and policymakers can use EpiPolicy to decide how to balance vaccinations with relaxing various forms of non-pharmaceutical interventions such as school closures, mass screening and contact tracing, and mask-wearing mandates.

Consider an outbreak in the fictitious country of the United Provinces (UP), which has a population of roughly one million people and 75% of the population are adults or seniors.

We will examine four specific interventions:

- ▸ School closures reduce the interaction between children in schools.
- ▸ Mass screening and contact tracing increase the transition rate from non-quarantined compartments (e.g. pre-symptomatic, I_{pre}) to quarantined ones (e.g. Q_{pre}), which have lower disease transmissibility rates.
- ▸ Mask-wearing mandates reduce the transmission rates in all facilities

except households because people don't wear masks in their homes.

▸ Vaccination moves individuals from the susceptible to the vaccinated compartment.

We simulate the effect of these interventions over one year from January 1st to December 31st. All interventions start on January 1st and last for four months with high intensity. We then explore the effect of relaxing to various degrees the non-pharmaceutical interventions until the end of the year. The higher the degree of relaxation, the less intensive these non-pharmaceutical interventions are. For example, with 100% relaxation everything returns to normal, meaning no further non-pharmaceutical interventions will be implemented. On the other hand, 0% relaxation implies all non-pharmaceutical interventions remain in force.

The vaccination drive runs throughout the year. The officials of UP wish to examine the impact of two vaccination drives: an aggressive, fast-rate drive where at most 4,500 adults or seniors are vaccinated every day, and a slow-rate one where at most 1,250 adults or seniors are vaccinated every day. The fast-rate drive vaccinates 70% of the adult and senior population within the first four months, while the slow-rate one only vaccinates 20% of adults and seniors within the same period. The fast-rate drive, however, comes with an added cost of 100 million dollars to set up the necessary distribution facilities and to secure a sufficient supply.

Tables 1 and 2 summarize the running dollar costs for implementing each intervention and the costs associated with the disease burden. For example, the cost of wearing a mask by an individual is \$0.05 a day and the cost of a hospital stay is \$250 per individual per day. These figures are purely illustrative and fictitious. A thorough region-specific, data-driven analysis is often required to determine appropriate intervention and disease burden cost estimates.

Determining which vaccination drive to choose is complicated by choice of how much to relax the other interventions. Policymakers often engage in a series of what-if analyses to determine a suitable intervention plan. Our officials at UP pose the following what-if questions:

What if we opt for:

▸ the cheaper slow-rate vaccination drive and relax the intensity of all other interventions by 100% (complete return to normal) by May?

▸ the more-expensive fast-rate vaccination drive and relax the intensity of all other interventions by 100% (complete return to normal) by May?

▸ the slow-rate drive but only relax the intensity of the other interventions by 50% by May?

▸ the fast-rate drive but only relax the intensity of the other interventions by 50% by May?

EpiPolicy enables UP's officials to quickly conduct such what-if analysis scenarios and compare the results of different intervention plans. Figure 1 shows EpiPolicy's visual dashboard for viewing the detailed results for scenario three of the four what-if analysis scenarios. Table 3 compares their outcomes in terms of total infections, deaths, and economic cost. From a dollar-cost economic perspective, a fast rate of vaccination with a complete return to normal appears to be the most economically promising intervention plan. However, a slower rate of vaccination needs to be balanced by applying other non-pharmaceutical interventions for a longer period with higher intensity (50% relaxation only).

One can explore other degrees of relaxation to better establish the relationship between the degree of relaxation, vaccination rate, and the overall disease and economic burden for different intervention plans. Figure 4 illustrates the outbreak can still be cost-effectively contained in UP with a slow vaccination rate if other non-pharmaceutical interventions are intensely applied.

Policymaking for epidemic control involves exploring the trade-offs of many intervention plans. This makes the process amenable to many computational optimization strategies that search for optimal plans to reduce overall infections and deaths while minimizing economic costs. We are currently exploring different optimization strategies including reinforcement-learning approaches to allow EpiPolicy to automate the search process for good intervention plans.

CONCLUSION

These examples illustrate how EpiPolicy can simulate a variety of what-if scenarios. The overall purpose of EpiPolicy is to support the policymaking process by enabling effective intervention planning discussions that are not hampered by code complexity, hidden parameters, or slow turnaround times when exploring alternatives. Given good data, clever planners, and political leadership responsive to science, future pandemics can be handled at less cost in life and treasure using tools like EpiPolicy. Computer scientists have a lot to bring to this very real-world application such as designing novel, algorithmic approaches to search for good intervention plans; developing high performance systems that can run millions of simulations and what-if analysis interactively; and designing collaborative and effective interfaces that support the complex process of policymaking to curb epidemics.

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