Theory of behavior-induced tipping points in the transmission of infectious diseases

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This material is based in part upon work supported by the National Science Foundation's Predictive Intelligence for Pandemic Prevention (PIPP) program under Grant No. 2200158: Heterogeneous Model Integration for Infectious Disease Intelligence

Abstract

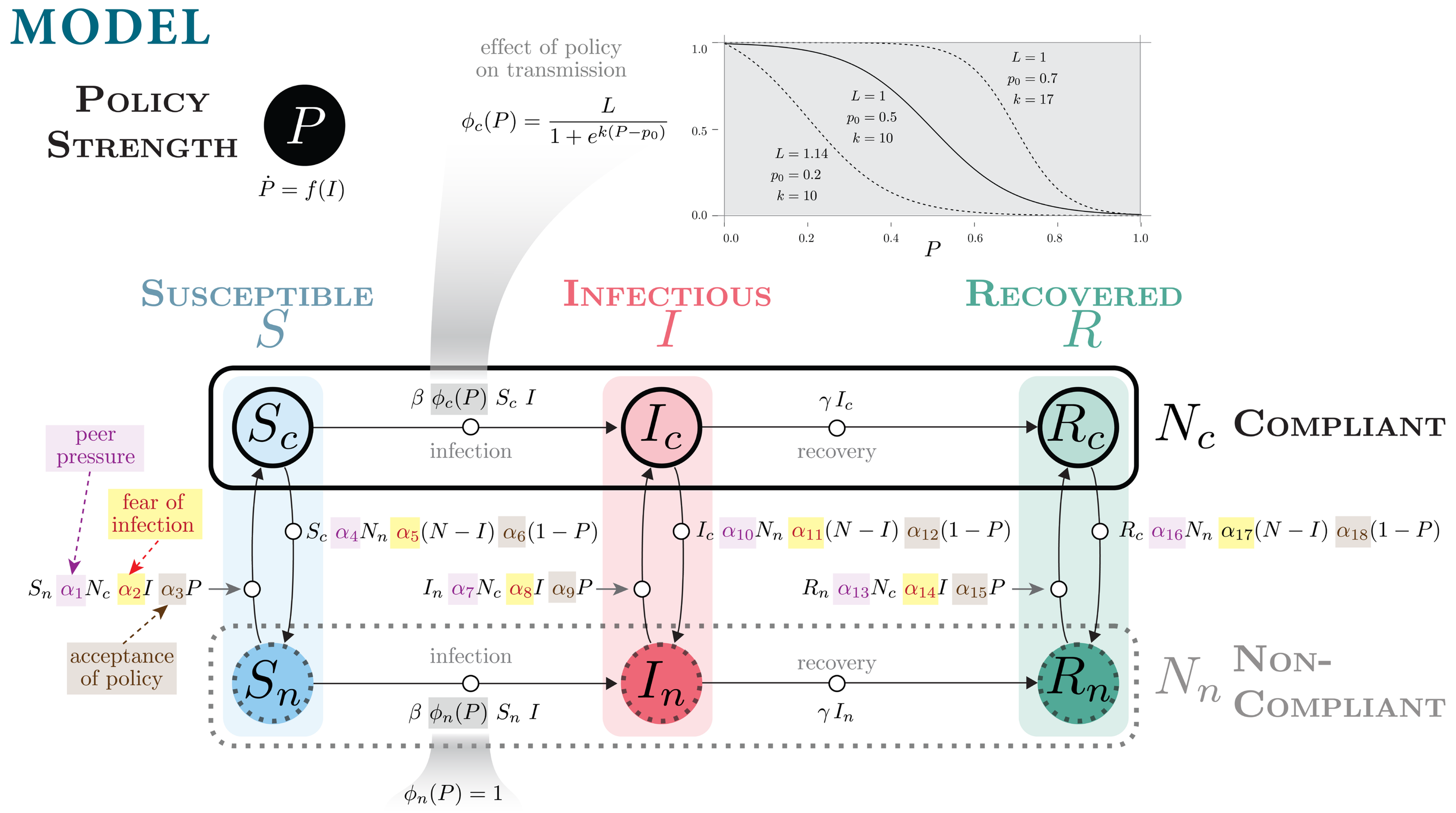
Behavioral feedbacks affect the transmission of infectious diseases. During outbreaks, various non-pharmaceutical interventions (NPIs) such as mask-wearing and social distancing may be effective in reducing the spread of infectious diseases, but not all members of a population may comply with public policies (Eikenberry *et al.* 2020, Ferguson *et al.* 2020).

Therefore, the coupling between changing behaviors and disease dynamics may be important for anticipating the effectiveness of public policies. We developed a compartmental model to understand the contemporaneous spread of disease within a population comprising compliant and non-compliant groups (Figs 1 & 2).

Model features

- SIR model with compliant and non-compliant subpopulations.
- Effect of policy intervention strength on transmission, modeled as a sigmoid with fittable parameters.
- Behavioral mechanisms (peer pressure, fear of infection, acceptance of policy) modeled as parameters mediating flow between compliant and non-compliant populations.
- Architecture allows for feebacks among policy strength, behavior, and infection dynamics.

1 MODEL



Model flow diagram. Policy strength $0 < P < 1$ is assumed to be a function of I. The effect of policy strength on transmission in compliant populations $\phi_c(P)$ is assumed to be sigmoid, and is modeled as a logistic function with fittable parameters L (least upper bound), k, (logistic growth rate) and p_0 (value of midpoint). Alternate functional forms are possible. Policy is assumed to have no effect on transmission in non-compliant populations, i.e. $\phi_n(P) = 1$. Behavioral parameters $0 < \alpha < 1$ mediate flows between complaint and non-compliant populations.

2 REPRODUCTION NUMBER

Basic Reproduction Number of the model is a function of basic transmission rate, recovery rate, equilibrium policy strength P^* ($dP/dt = 0$), and compliance-dependent effect of policy on behavior (Diekmann *et al.* 2010).

transmissibility

compliance-dependent effect of policy on transmission

$$\mathcal{R}_0 = \frac{\beta}{\gamma}\left[\phi_c(P^*)N_c + \phi_n(P^*)N_n\right]$$

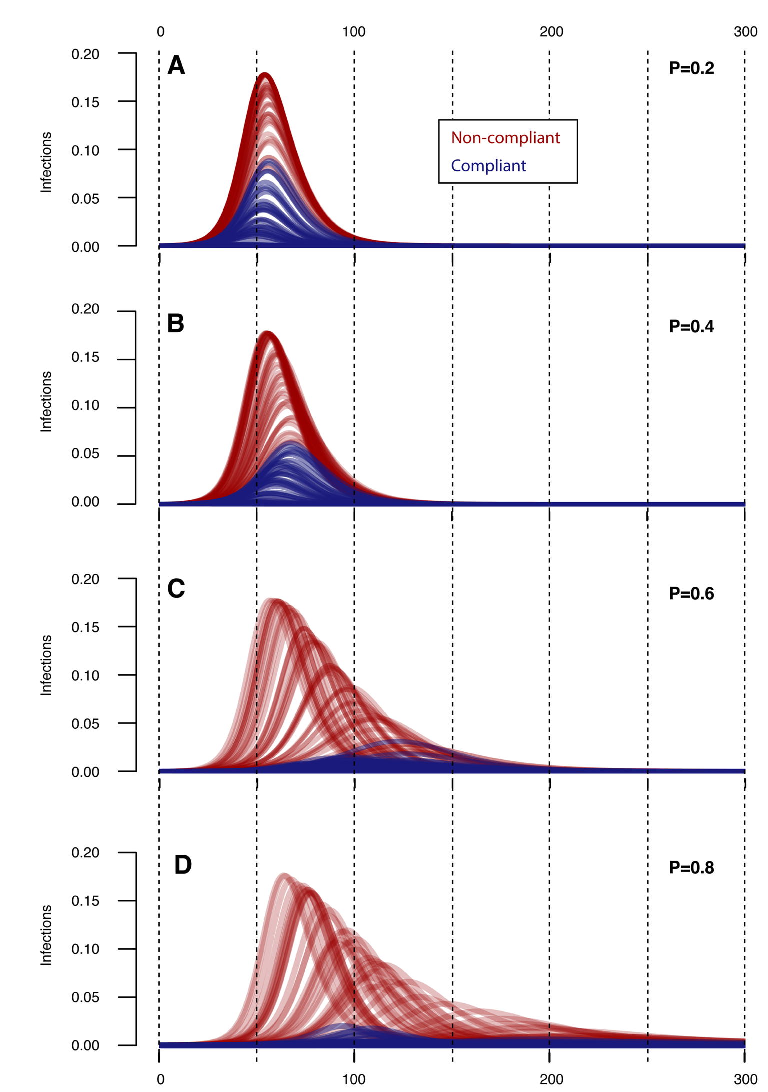
recovery rate

compliant & non-compliant populations

Results

We examined the effect of policy strength on **infection dynamics**, using fixed policy P, fixed parameters of $\phi_c(P)$ and Latin hypercube sampling of epidemiological and behavioral parameters (Fig 3). We also studied the effect of policy strength on **peak prevalence and time to extinction**, indicators of infectiousness and disease persistence, respectively (Fig 4) (Allen 2008, Barbour 1975).

3 EFFECT OF POLICY STRENGTH ON INFECTION DYNAMICS



Time evolution of disease dynamics for various policy strengths. Policy strength has a significant impact on timing and duration of disease outbreaks.

Blue and red curves represent infections in compliant and non-compliant populations, respectively.

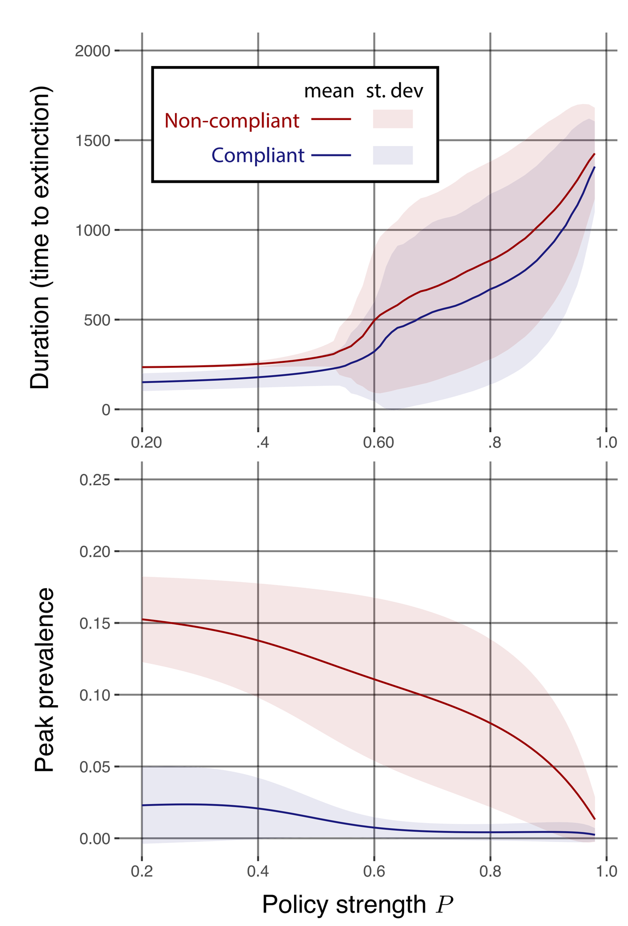
The policy strengths are :
(A) $P = 0.2$, **(B)** $P = 0.4$, **(C)** $P = 0.6$, **(D)** $P = 0.8$.

The initial conditions are:
$Sc = 0.4999$, $Ic = 0.0001$, $Rc = 0$, $Sn = 0.4999$, $In = 0.0001$, $Rn = 0$.

Parameters of $\phi_c(P)$ are:
$L = 1$, $k = 10$, and $p_0 = 0.5$

All other parameters are taken from the Latin hypercube sampling with $n = 500$.

4 EFFECT OF POLICY STRENGTH ON DISEASE PERSISTENCE & PEAK PREVALENCE



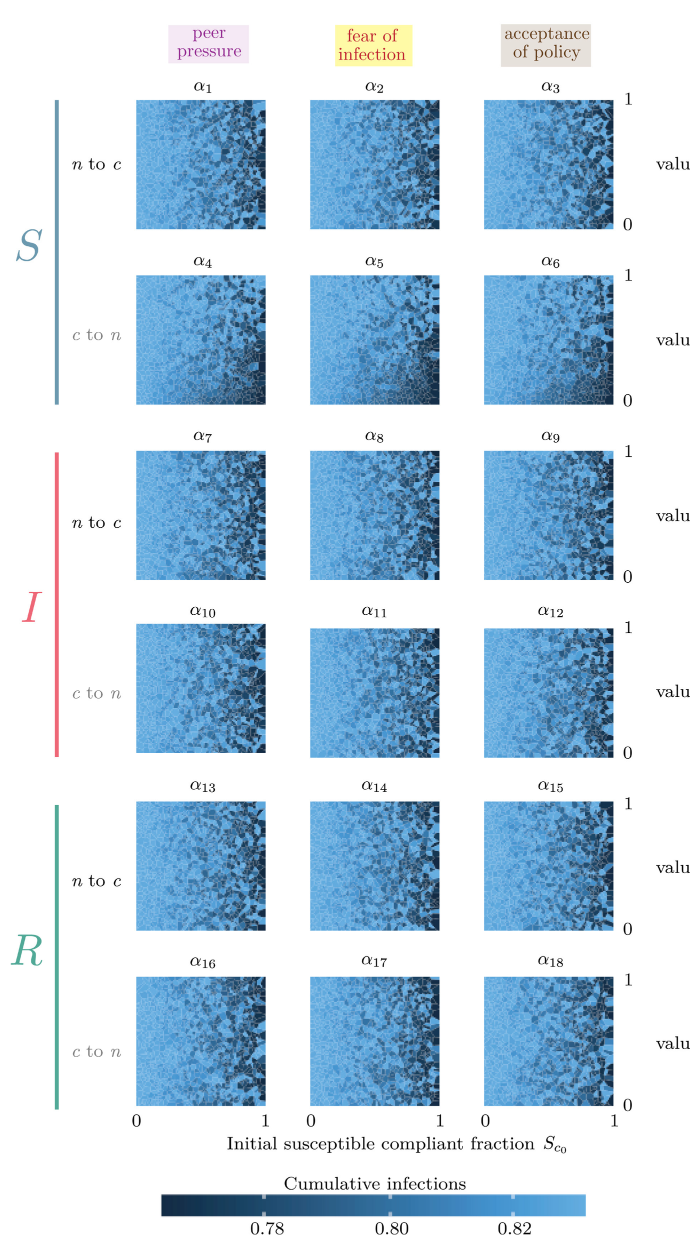
Disease persistence (time to extinction) and peak prevalence as functions of policy strength P. As modeled, policy strength above a threshold has a significant and non-linear impact on disease persistence (time to extinction) and peak prevalence.

Blue and red curves represent infections in compliant and non-compliant populations, respectively. Solid lines are the mean values over 1000 simulations using Latin hypercube sampling of parameters. Bands represent the standard deviation across simulations.

The results are consistent with the concept of "flattening the curve" that entered the popular lexicon during the COVID-19 pandemic (i.e., that interventions reduce peak prevalence at the cost of extending the outbreak in time.

We conducted sensitivity analysis to explore the sensitivity of **outbreak size** (cumulative infections) to **behavioral parameters α** and **initial fraction of population in the susceptible compliant class S_c** (Figs 5 & 6).

5 DEPENDENCE OF OUTBREAK SIZE ON BEHAVIOR



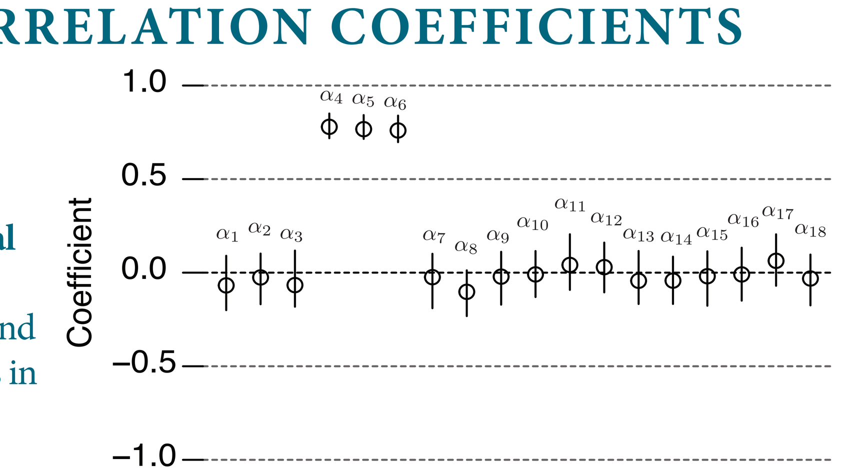
Dependence of outbreak size (cumulative infections) on behavioral parameters α and initial compliant susceptible fraction. Sensitivity analysis, with policy strength fixed at $P = 0.3$. Behavioral and epidemiological parameters and initial conditions were drawn from Latin hypercube sampling with $n = 1000$.

We observe a monotonic increase in cumulative infections for all parameters with decrease in initial fraction of compliant susceptibles.

We also observe a monotonic effect on outbreak size of peer pressure, fear of infection, and policy acceptance among susceptibles, especially parameters α_4, α_5, and α_6, which mediate the flow from compliant to non-compliant susceptibles. This shows that change in compliance among susceptibles, especially loss of compliance, has the greatest impact on outbreak size, and suggests that measures reinforcing compliance (preventing a decrease in compliance) in already compliant populations may be useful in reducing outbreak sizes.

6 CORRELATION COEFFICIENTS

Partial rank correlation coefficients for behavioral parameters. Simulations and parameters as in Fig. 5.



Conclusions

- Non-pharmaceutical interventions can have a significant effect on the timing and severity of disease outbreaks in populations with varying proportions of compliant and non-compliant individuals. Effects may be non-linear.
- Peer pressure, fear of infection, and degree of compliance can have a significant impact on disease dynamics, especially in the subpopulation of compliant, susceptible individuals.
- Policies aimed at preventing initially compliant (and susceptible) individuals from rejecting interventions may be most effective at reducing the impact of disease outbreaks.

Next Steps

- Implement and study feedback between infection level I and policy strength P.
- Determine how to fit the model to empirical epidemiological, behavioral, and policy data.

References

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