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Cite this article: Espinoza B, Saad-Roy CM, Grenfell BT, Levin SA, Marathe M. 2024 Adaptive human behaviour modulates the impact of immune life history and vaccination on long-term epidemic dynamics. *Proc. R. Soc. B* **291**: 20241772.
https://doi.org/10.1098/rspb.2024.1772

Received: 19 March 2024
Accepted: 23 August 2024

Subject Category:
Biological applications

Subject Areas:
behaviour, health and disease and epidemiology

Keywords:
adaptive behaviour, epidemic modelling, immune life history, multi-scale modeling

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Electronic supplementary material is available online at https://doi.org/10.6084/m9.figshare.c.7481230.

Adaptive human behaviour modulates the impact of immune life history and vaccination on long-term epidemic dynamics

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The multiple immunity responses exhibited in the population and co-circulating variants documented during pandemics show a high potential to generate diverse long-term epidemiological scenarios. Transmission variability, immune uncertainties and human behaviour are crucial features for the predictability and implementation of effective mitigation strategies. Nonetheless, the effects of individual health incentives on disease dynamics are not well understood. We use a behavioural-immuno-epidemiological model to study the joint evolution of human behaviour and epidemic dynamics for different immunity scenarios. Our results reveal a trade-off between the individuals' immunity levels and the behavioural responses produced. We find that adaptive human behaviour can avoid dynamical resonance by avoiding large outbreaks, producing subsequent uniform outbreaks. Our forward-looking behaviour model shows an optimal planning horizon that minimizes the epidemic burden by balancing the individual risk–benefit trade-off. We find that adaptive human behaviour can compensate for differential immunity levels, equalizing the epidemic dynamics for scenarios with diverse underlying immunity landscapes. Our model can adequately capture complex empirical behavioural dynamics observed during pandemics. We tested our model for different US states during the COVID-19 pandemic. Finally, we explored extensions of our modelling framework that incorporate the effects of lockdowns, the emergence of a novel variant, prosocial attitudes and pandemic fatigue.

1. Introduction

Transmission, immune uncertainties and human behaviour are three key features of infectious diseases that are crucial for the predictability and implementation of effective mitigation strategies [1]. Recent work has underlined the importance of transmission and immune uncertainties for future pandemic dynamics. In particular, simple immuno-epidemiological models revealed that the strength and duration of natural and vaccinal immunity have the potential to produce a large range of medium- and long-term epidemiological scenarios [2,3]. Subsequently, model extensions were used to study potential epidemiological and evolutionary dynamics with different vaccine dosing regimes [4], in addition to the potential

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implications of vaccine nationalism [5], and the impacts of accumulating immunity [6].

Together, immuno-epidemiological dynamics and pathogen evolution generate a number of complexities that impact infectious disease dynamics (e.g. see [7,8]). Additionally, as seen throughout the 2009 influenza A (H1N1) pandemic, the 2014 West African Ebola virus disease (EVD) epidemic and the ongoing COVID-19 pandemic, a crucial factor that contributes to epidemic complexity is human behaviour [9,10]. The interplay between human behaviour and epidemics, mediated by endogenous feedback processes, is well recognized. Understanding these feedback processes and elucidating their outcomes requires characterizing behavioural responses and the associated incentives [11–14]. Behavioural heterogeneity arises over time and across regions, driven by socio-economic composition, cultural and political polarization, among other factors [15,16]. In turn, behavioural heterogeneity has a crucial impact on long-term trajectories. For example, adaptive human behaviour has been a key component in modulating transmission, and its impact has been extensively documented in multiple regions during the ongoing pandemic [17,18]. In general, adaptive behavioural responses against infection arise due to the interdependence between individuals' necessity to maintain social interactions and economic productivity, while minimizing their infection risk. Furthermore, variations in the individuals' immune profile may modulate their infection risk, which consequently can also induce differential behavioural responses.

Despite increasing efforts on understanding the complex repercussions of behavioural responses during epidemics, significantly less attention has been given to modelling the fundamental challenge of disease outbreak detection. Disease surveillance systems are critical for achieving early warning and, provide valuable time to respond to emerging biological threats [19,20]. Disease outbreak detection represents a tipping point that triggers emergency declarations, information dissemination, adaptive behavioural responses and deployment of public health interventions [21,22].

While prior work has examined the role of host immune responses on potential post-pandemic trajectories, the concurrent impacts and dynamics of human behaviour remain as outstanding questions. In this study, we examine these questions with a behavioural-immuno-epidemiological model. We begin by schematically outlining the model framework. We examine the multiple long-term dynamics scenarios generated by the feedback between different levels of behavioural adaptations and the strength of immune responses. Our results show that behavioural responses can avoid dynamical resonance by avoiding large outbreaks, producing subsequent uniform outbreaks. Furthermore, our forward-looking behaviour model exhibits an optimal planning horizon that minimizes the epidemic burden by balancing the individual risk–benefit trade-off. Moreover, we find that strong behavioural adaptations can compensate for heterogeneous immunity responses, producing that epidemics with different immunity profiles would exhibit similar disease dynamics. Finally, as a case study, we use mobility data during the COVID-19 pandemic from multiple US states as a proxy to test our adaptive behavioural model. With the calibrated behaviour model, we studied the empirical and expected interactions of behavioural responses and host immunity on epidemic dynamics. Extensions of our modelling framework that incorporate the effects of lockdowns, the emergence of a novel variant, voluntary reduction of contact rates by infected individuals, pandemic fatigue, information delay and disease surveillance systems, are also explored in electronic supplementary material, appendix.

2. Model framework

We couple simple models of immuno-epidemiology and adaptive human behaviour, with three key components: (i) *New York City climate-dependent transmission* incorporating seasonal changes in the magnitude of transmission [23]; (ii) *differential infection and immunity phenotypes*, depending on individuals' exposure history [2,4]; and (iii) *heterogeneous behavioural adaptations*, which depend on individuals' infection risk according to their health-state [24–26]. Thus, our framework incorporates processes acting at different scales, from within hosts (differential susceptibility or infectiousness depending on individuals' exposure history), to individuals (behavioural decisions driven by the expected infection risk and the benefits of social activity) and finally to populations (availability and effectiveness of vaccination, modulating population-level immunity).

To model adaptive human behaviour, we follow prior literature [24–26] and assume that, each day, an individual is simultaneously seeking to increase contacts (in order to maximize the benefits secured through social interactions), while minimizing its infection risk (by reducing contacts). We assume that economic productivity depends on social interactions [27,28] and, we use contacts as the mechanism by which behaviour is adapted, disease is transmitted and benefits are acquired. Finally, the daily decision process evaluates the expected current and future costs/benefits based on a future projection over a finite planning horizon, as well as potential future transitions to alternative infectious or (partially) immune states. Note that we assume fully immune or infected individuals do not have incentive to behave strategically, and these individuals therefore make the daily number of contacts that maximizes the net benefits. We model heterogeneous behavioural responses by coupling a set of decentralized Markov decision processes, formalized via a set of Bellman equations. Our model framework is schematically outlined in figure 1, and the detailed mathematical formulation of the behavioural model via the specific immune phenotype's optimization problems is in the electronic supplementary material, appendix.

Figure 1*a* illustrates the coupling between the disease progression model and the adaptive behaviour model. Each day, the current disease prevalence gives the risk of infection associated with make different number of contacts for susceptible individuals. However, while contacts pose a risk of infection, they also impart benefits. Thus, the trade-off between increasing contacts to gain utility and decreasing contacts to reduce the infection probability defines a dynamic optimization problem over the course of the epidemic. In our model, the decision making process, based on the current health distribution of the population and on the future projection over a defined planning horizon, is potentially distinct for each class of susceptible individuals. Furthermore, across the classes of susceptible individuals and depending on the immunity profiles of the population, the adaptive behaviour model may exhibit homogeneous or heterogeneous behavioural responses (see figure 1*b*).

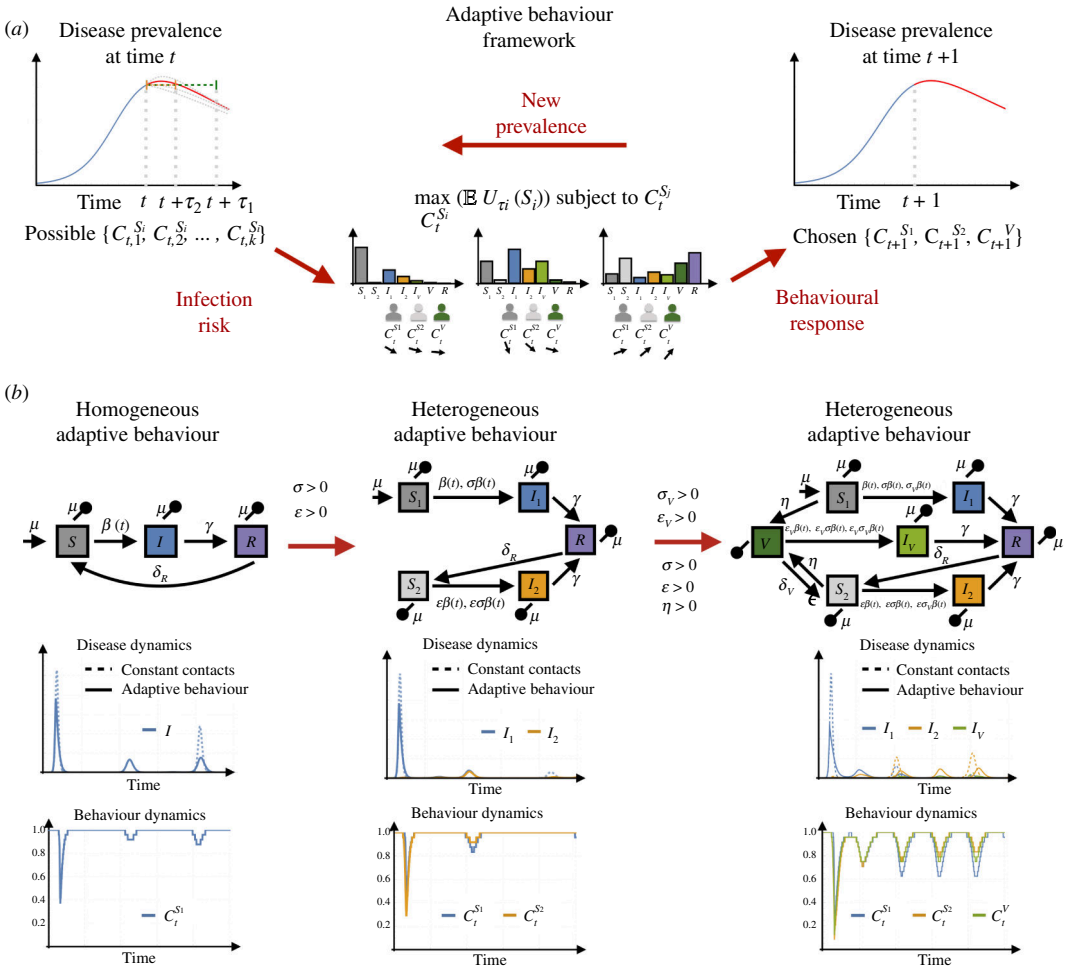

Figure 1. Schematic of the modelling framework components. We couple an epidemic model and a model of heterogeneous adaptive human behaviour driven by distinct immunity phenotypes. (*a*) Individuals modulate their daily activity level according to the infection risk perceived, which in turn reshapes the epidemic trajectory. The epidemic model incorporates individuals' immune life history and vaccination; where S_1 and S_2 denote the fully and partially immune susceptible individuals, I_1 and I_2 denote the primary infected and reinfected individuals, V and I_V denote the vaccinated and infected vaccinated populations and, R denotes the fully immune individuals. (*b*) Each immunity scenario induces different disease and behavioural dynamics (shown for the constant contacts model in dashed lines and, for the adaptive behaviour model in thick lines).

To incorporate a seasonal force and in the absence of behaviour (i.e. the 'constant-contacts model'), we assume that the transmission is climate-dependent and we use a seasonal transmission likelihood derived from the New York City climate [2,23]. As in [2], we assume that vaccination begins 1.5 years after the index case with a weekly rate of 1% ($\eta = 0.0014$ per day). Since the dynamics of our coupled behavioural-immuno-epidemiological model hinge on the individual contact rates chosen at each day, we use the per-contact likelihood of infection ($C^*\hat{\beta}(t) = \beta(t)$, where C^* is the maximum contact rate). That is, in the absence of behavioural adaptations, transmission follows the derived New York City's seasonal transmission likelihood, while the adaptive model modulates this via adjustment of the number of contacts. In the electronic supplementary material, appendix, we explore the impact of varying these behavioural parameters.

3. Epidemic model

Similar to the work in [2], we use an SIRSI-like model incorporating three immunological profiles: completely susceptible S_1, partially immune individuals S_2, and fully immune individuals R, due to previous infection or vaccination. Infected individuals are divided into first time infected individuals I_1, and reinfected individuals I_2, and breakthrough infections I_V. Individuals are recruited being fully susceptible (S_1), and the population is maintained constant, so that birth and natural death rates balance (μ). Fully susceptible population may get the vaccine at a rate η or may get infected by making contacts with first-time or reinfected individuals at a baseline likelihood β and $\sigma\beta$, respectively. Recovered individuals from first and reinfection are assumed to have full immunity that wanes on average after $1/\delta_R$ days. Moreover, we assume vaccinated individuals' immunity wanes on average after $1/\delta_V$ days. After natural or vaccine acquired immunity wanes, susceptible individuals S_2 are assumed to show partial immunity, $0 < \epsilon < 1$. Partially immune susceptible individuals (S_2) get reinfected by contacting either first-time infected (I_1) or reinfected individuals (I_2) with likelihoods $\epsilon\beta$ and $\epsilon\sigma\beta$, respectively. The aforementioned model of disease progression is sketched in figure 2 and formalized by the following set of equations.

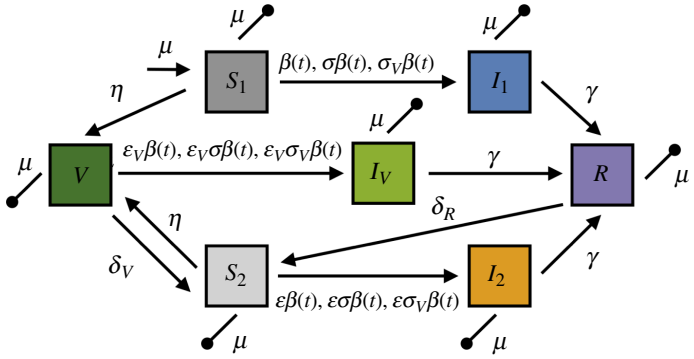

Figure 2. Schematic representation of the SV IRSI model flows for fully susceptible (S_1), vaccinated (V), infected vaccinated (I_V), first time infected (I_1), partially immune (S_2), reinfected (I_2) and recovered individuals (R).

$$\begin{aligned}
\dot{S}_1 &= \mu N - \beta(t) S_1 \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - \mu S_1 - s_V \eta S_1,\\
\dot{V} &= s_V \eta (S_1 + S_2) - \epsilon_V \beta(t) V \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - (\delta_V + \mu) V,\\
\dot{I}_V &= \epsilon_V \beta(t) V \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - (\gamma + \mu) I_V,\\
\dot{I}_1 &= \beta(t) S_1 \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - (\gamma + \mu) I_1,\\
\dot{R} &= \gamma (I_1 + I_2) - (\delta_R + \mu) R,\\
\dot{S}_2 &= \delta_R R - s_V \eta S_2 - \epsilon \beta(t) S_2 \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - \mu S_2,\\
\dot{I}_2 &= (\epsilon \beta(t) S_2 + \epsilon_V \beta(t) V) \frac{I_1 + \sigma I_2 + \sigma_V I_V}{N} - (\gamma + \mu) I_2 .
\end{aligned}$$

The set of parameters used in our numerical experiments, unless otherwise indicated, are collected in table 1.

4. Results

(a) Adaptive human behaviour can homogenize future outbreaks

We examine the interplay between adaptive behaviour and the strength of immune responses on epidemic dynamics. For the epidemic model with and without behaviour, figure 3*a–c* illustrates the time courses for primary infections (I_1), reinfections (I_2) and infections in vaccinated individuals before vaccinal immunity has waned (I_V), under different scenarios of relative susceptibility after immunity has waned (ϵ). Figure 3*d* shows how the time series of associated activity levels changes with increasing sensitivity to infection risk (i.e. from null adaptation to strong behavioural responses). As described in detail in [2], without adaptive behaviour, the strength of immunity (captured via the relative susceptibility to secondary infection) can give rise to a large range of medium-term dynamics (figure 3*a*), including sizable secondary peaks. In contrast, strategic behaviour of susceptible individuals decreases the likelihood of large subsequent outbreaks and leads to uniform future outbreaks sizes with inter-outbreak periods that follow the yearly seasonal forcing (figure 3*b,c*). Thus, regardless of the strength of host immunity, behavioural responses that are driven by constant risk sensitivity over time tend to normalize inter-epidemics periods and peak sizes of subsequent outbreaks.

The intuition behind this result is that behavioural adaptation tends to manage infections over time and across immunity profiles. In turn, such 'management' prevents the formation of big susceptible pools (that would give rise to big outbreaks) and therefore gives smaller periodic outbreaks. However, this effect comes at a cost to fully susceptible individuals: they must increase their efforts (significantly decrease contacts) to avoid a primary infection. On the other hand, due to immunity obtained from a primary infection, partially susceptible individuals (S_2) can relax their behavioural responses. Finally, note that these results are also modulated by the duration of natural and vaccinal waning immunity, as well as the infection risk sensitivity. We explore the effects of variations in infection risk sensitivity (ν) in the electronic supplementary material, appendix.

(b) Optimal planning horizon reduces the pandemic size

In our model, the decision-making process for behavioural adaptation depends on the current and expected benefits of maintaining social interactions during a predefined planning horizon. In figure 4*a*, we explore the impact of the planning horizon length (τ) on epidemic dynamics. For this analysis, we assume that the planning horizon is fixed over time and homogeneous across immune phenotypes. Our simulations illustrate the impact on the epidemic dynamics of varying the planning horizon for individuals with different immune phenotypes (S_1, S_2 and V). Our results show that variations in the

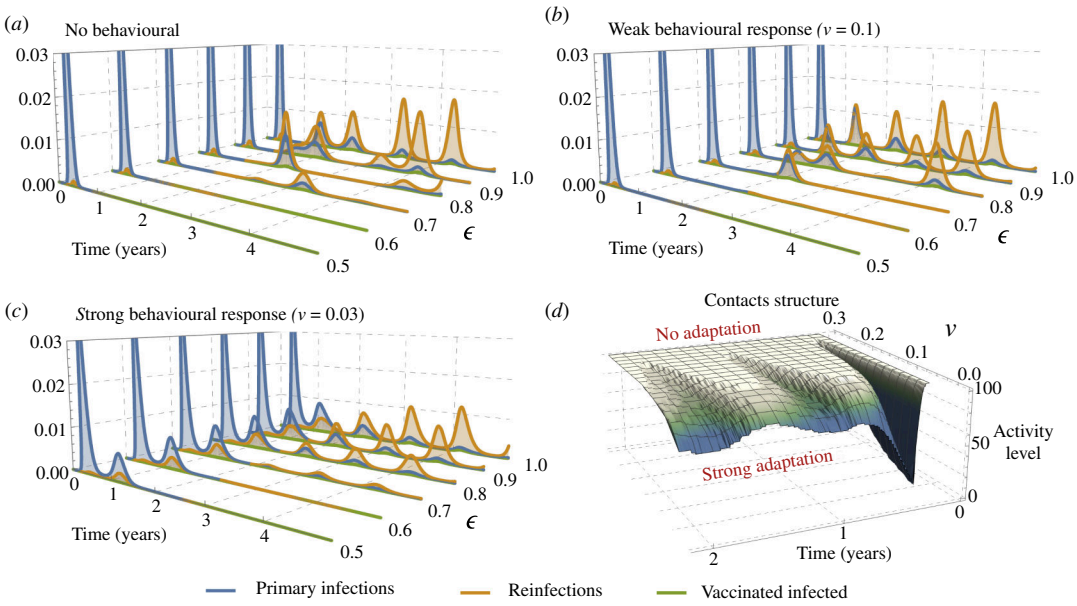

Figure 3. Strong adaptive behaviour homogenizes future outbreaks. First-time infections (I_1), reinfections (I_2) and infections after vaccinated (I_V), time courses for varying partial immunity scenarios under (*a*) the constant contacts model, and (*b–c*) under adaptive behaviour. Strong behavioural adaptations ($v = 0.1$ and $v = 0.03$) tend to uniform future outbreaks and produce inter-outbreak periods driven by the seasonal force of infection. We calibrated the model using the rest of model parameters as indicated in table 1.

Table 1. Constant contact rates and adaptive behaviour model baseline parameters.

Par.	description	value	ref
μ	birth rate	$0.02y^{-1}$	[2]
β	likelihood of infection	varies	[23]
ϵ	natural reduced susceptibility	varies	—
ϵ_v	vaccine reduced susceptibility	varies	—
σ	reduced infectiousness	varies	[2]
σ_v	vaccine reduced infectiousness	$[0.1 - 0.5]$	[2]
γ	recovery rate	1/5	[2]
δ_R	natural waning immunity	$1y^{-1}$	[2]
δ_V	vaccine waning immunity	$\frac{1}{30(9)}$	[2]
η	vaccination rate	1% week^{-1}	[2]
s_v	vaccination starting time	1.5y	[2]
v	utility function shape parameter	0.1	[24]
δ	discount factor	0.99986	[24]
b	max. number of contacts (day)	48	[24]
τ	planning horizon length	varies	-

planning horizon dramatically impact the initial 'pandemic' size (left panel). Particularly, a planning horizon of two weeks highly decreases the magnitude of the first outbreak relative to other planning periods we examined.

Extremely short or long planning horizons bias the individual risk–benefit trade-off, thus leading to high infection levels. The intuition that underpins this result is as follows. First, short planning horizons tend to lead to individuals erroneously underestimating the utility loss during the entire infectious period. On the other hand, long planning horizons also tend to undervalue potential utility losses during infection by weighting the utility obtained during longer stages (i.e. susceptible and recovered) [25]. Behavioural responses can also be modulated by the implementation of government actions (vaccination, social distancing or other policies), which would shape the perceived risk–benefit trade-off [29]. While a planning horizon of two weeks substantially reduces the magnitude of the initial peak, this causes subsequent medium-sized post-pandemic outbreaks. In this scenario, the single peak initial outbreak produced in the absence of behavioural responses (see figure 3*a*), is reshaped to a bi-modal outbreak due to a distribution of infections over time (figure 4*a* (right)). Moreover, we find that long planning horizons tend to produce big and sparse outbreaks as in the model without behavioural adaption, see for instance, the disease dynamics shown in figure 4*a* (right) for planning horizons of 8 or 10 weeks.

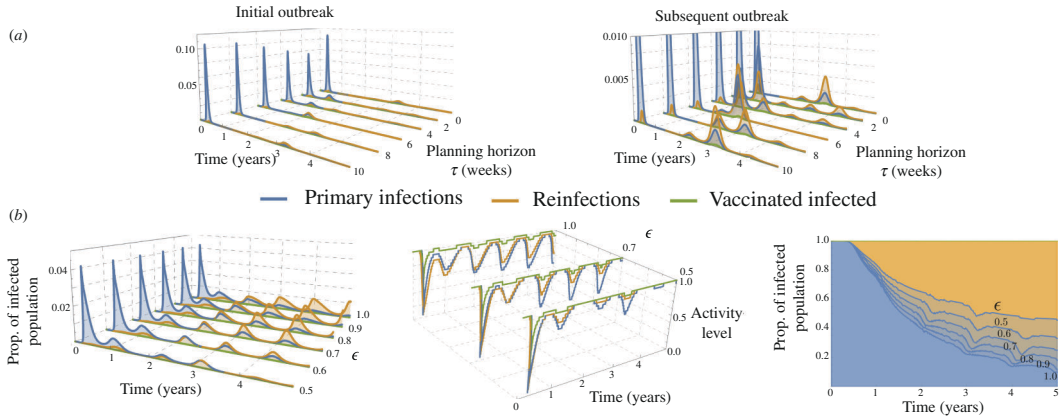

Figure 4. (*a*) The optimal planning horizon minimizes the initial outbreak's peak size. (*b*) Strong adaptive behaviour compensates for the impact of differential immunity. Panel (*a*) shows that there exists a best planning horizon ($\tau \approx 2$ weeks) that minimizes the initial outbreak's peak size. Short and long planning horizons do not appropriately weight the risk–benefit trade-off of avoiding risk of infection and increasing benefits by making contacts. Moreover, different planning horizons produce distinct outbreaks landscape. We calibrated the model assuming $\nu = 0.05$ and the rest of parameters as indicated in table 1. Our simulations in panel (*b*) show that in the absence of vaccination, a two weeks planning horizon and strong adaptive behaviour produce subsequent outbreaks exhibiting uniform sizes and inter-epidemic periods, regardless of the partial immunity granted by previous infections (left). This equalizing effect across partial immunity levels is modulated by the heterogeneous behavioural adaptations, which are driven by the health-specific infection risks (centre). It follows that epidemics with different immunity landscapes would exhibit similar disease dynamics (right). We calibrated the model assuming $\{\nu, \tau\} = \{0.05, 14\}$ and the rest of parameters as indicated in table 1.

Our results show that the impact of the planning horizon is mostly exhibited in the pandemic phase, where extremely high infection levels are expected. After the initial peak, the epidemiological and behavioural dynamics tend to exhibit less variation in epidemic peak sizes and inter-epidemic periods, with some scattered big outbreaks. Note that this is heavily driven by our assumption of a time-independent risk sensitivity, which models individuals equally valuing their contacts over time. However, in reality, the perceived value of social interactions may quickly change due to many different factors, like fear, awareness, control policies compliance, fatigue and socio-economic stress, among other factors. In turn, this would adjust the individual level risk–benefit trade-off and thus consequently impact epidemic dynamics. We explore the impact of waning risk sensitivity in the electronic supplementary material, appendix.

(c) Behavioural adaptations compensate heterogeneous immunity responses

We explore the impact of different immunity levels acquired after infection (ϵ), on the daily behavioural responses and the disease dynamics. The important result is that highly distinct population immunity landscapes may generate similar epidemic dynamics, where behavioural responses balance the impact of immunity variations. Figure 4*b* (left) depicts the disease dynamics for varying reinfection susceptibility levels. We found that behavioural adaptations change according to the population's immunity characteristics, across immunity landscapes. This in turn modulates the disease progression, producing similar disease dynamics. Our simulations in figure 4*b* (centre) show that for low levels of acquired immunity ($\epsilon \approx 1$), the equalizer effect is achieved under strong behavioural responses. In contrast, for high levels of acquired immunity ($\epsilon \approx 0.5$), weak behavioural adaptations can attain similar disease dynamics. Moreover, we found that the response of the partially susceptible populations differ for the different immunity scenarios assumed. Specifically, when low immunity is acquired after infection, the contact rates of the partially immune individuals mimic that of the fully susceptible ones (figure 4*b*, for $\epsilon \approx 1$). In contrast, when high immunity is acquired after infection, the contact rates of the partially immune individuals tend to follow the corresponding to vaccinated individuals (figure 4*b*, for $\epsilon \approx 0.5$). The previous observation follows from our assumption of a highly effective vaccine. Finally, the proportion of reinfections increases as the acquired immunity after infection decreases (figure 4*b* (right)). In other words, in the scenario of low (high) immunity acquired after infection, the long-term epidemic is mainly driven by reinfections (primary infections). Consequently, the expected behavioural responses are driven and drive the immunity landscape, potentially producing that epidemics with different immunity landscapes exhibit similar dynamics.

(d) COVID-19 epidemic in some US states: a case study

We compare behavioural responses derived from our adaptive model with empirically observed population mobility data as a proxy of behavioural response. We fit average contact rates of susceptible from the adaptive behaviour model to averages of daily mobility data that involve social interactions, for the states of New York, Massachusetts, Washington, Texas, California and Arizona. Surprisingly, we find that our simple model can adequately capture complex empirical behavioural dynamics observed. We tested our behaviour model using different US states during the COVID-19 pandemics, under a range of settings (figure 5). Note that while our model focuses on endogenously driven individual behaviour, the empirical data reflect behavioural changes produced by a combination of endogenous and exogenous mechanisms, centralized mandates and decentralized behavioural decisions, along with a set of heterogeneities across regions (see §5). In reality, the dramatic initial drop on the population's activity was mostly driven by centralized mandates and exogenous information, which produced a behavioural

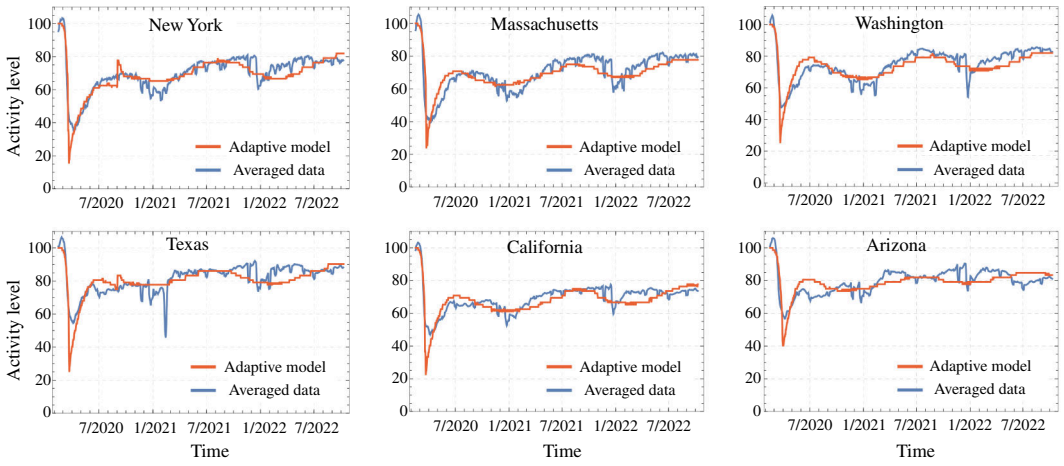

Figure 5. State-specific mobility data (in blue) and fitted mean activity level of susceptible and vaccinated populations derived from the adaptive model (in red). We use the Google COVID-19 Community Mobility Reports data as a proxy for the population's activity. Specifically, we consider the mean of the weekly activity reported for the categories *retail and recreation*, *transit stations* and *workplaces*. We found the fitting results to be highly sensitive to the assumed population's immunity profile. Interestingly, the fitting results improve when assumed short natural waning immunity periods of around three months. We fitted the behavioural parameters ν and τ, and calibrated the epidemic model assuming the parameters in table 1.

response disproportional to the low infection risk experienced at that time. While our model of behavioural response was able to reproduce the initial drop in the activity level, the behavioural response is driven by high prevalence levels, which were not experienced in reality. After the initial strong response, our model was able to capture the seasonally driven mobility rates exhibited by the empirical data for most of the selected states (see electronic supplementary material, appendix).

5. Caveats

The proposed epidemic and behavioural models made several simplifying assumptions. Following the work by Saad-Roy *et al*. [2], we model immune responses by considering only primary infections, infections of vaccinated individuals and reinfections. The epidemic model simplifies the population's heterogeneities such as infection severity [30], regional mobility and health disparities [31,32], age structure [33,34], vaccination regimes [5,35] and superspreading events [36,37], among other documented factors. Furthermore, the impact of infections produced by asymptomatic individuals is not considered [38], and the complex immune dynamics generated by co-circulating variants are not incorporated [1,39]. We assume seasonal transmission similar to the one exhibited by the betacoronavirus HKU1 (HCoV-HKU1) [2,23]. The model assumes a single immunization tier, with constant rate vaccination starting one and a half years after the beginning of the infectious process onset. The impact of multiple vaccination regimes and differential effectiveness against variant-specific infection is not incorporated [40].

On the other hand, our behavioural model incorporates individual adaptive behaviour via contact rate modulation. Other behavioural responses such as mask wearing [41], voluntary vaccination or testing [42,43] and behavioural dichotomy [44], are not explicitly incorporated. Furthermore, we ignore individual decision-making regarding adherence to a particular intervention, this could be modelled via game-theoretic approaches (e.g. [45–47]). It is known that behavioural choices regarding compliance with interventions would lead to complex dynamics. Imperfect vaccination could show bistability on behavioural decisions depending on the vaccine's effectiveness and cost [48]. Moreover, social distancing is known to induce oscillatory dynamics between disease prevalence and behavioural decisions, depending on the cost–benefit trade-off [49]. The simple population structure assumed prevents us to incorporate the impact of sociocultural and economic determinants, as well as the role of empathy or social group affinities [16,26,50]. We model the decision-making process exclusively driven by infection risk aversion, based on the expected private benefits of social interactions and costs of infection during a planning horizon. Our behaviour model assumes the population plan ahead using a fixed planning horizon, where the sensitivity to infection risk remains constant over the epidemic period. Individuals neglect the impact that their behavioural decisions impose on others, the effects of empathy or social group affinities are not incorporated in the decision-making process. Individuals risk assessment is based on endogenous, reliable and complete information, and do not incorporate many factors or information sources that would generate or shift social dynamics during pandemics [13,51–55]. We suppose individuals have perfect knowledge of their own health class and the health class of others. We assumed information is immediately available and we do not consider the impact of information accuracy and availability. Our model does not incorporate the different constraints faced by individuals with limited capacity to respond, for instance, due to low incomes. Consequently, individuals' are assumed to have access to unlimited resources, which results in continuous and unconstrained adaptive behavioural responses. In this scenario, susceptible individuals would reduce their contact rates as much as required by the cost–benefit trade-off, during the required period. In reality, however, factors like economic stress and loss of work [56–58], pandemic fatigue or risk sensitivity decay [59], may restrict the exhibited behavioural response of susceptible individuals over time. Our model does not account for the impact of beliefs and personal knowledge about the epidemic, as these factors are recognized to have a big impact on individuals' behavioural decisions [60,61].

6. Discussion

We formulate a behavioural-immuno-epidemic model to examine the interplay between adaptive human behaviour and potential immunity landscapes produced on the mid- and long-term pandemic dynamics. We explore the impact of individual-level behavioural responses driven by the risk of infection and immune response. Our model shows that risk-based behavioural adaptations are effective on avoiding high prevalence levels, particularly during the early phase of the epidemic, when most of the population is fully susceptible. Our results show that sustained strategic behaviour of susceptible, partially susceptible and vaccinated individuals in general reduces the likelihood of large outbreaks. By reacting to the dynamic infection risk depending on their immune-specific risk perception, individuals reshape epidemic dynamics by dynamically modifying their structures of contacts. Consequently, large outbreaks avoidance produces uniform subsequent outbreaks with inter-outbreaks periods driven by the seasonal infection force, due to the distribution of infections generated over time.

In countries where mandates rely on decentralized governance systems, variations in behavioural responses over time and across geographical regions are expected. Previous studies have shown that even when similar policies are implemented, variation in responsiveness lead to different outcomes [12]. Moreover, political polarization and other trends involving individual-level decisions (like vaccination, mask-wearing, social distancing, etc.) may tend to expand behavioural heterogeneities in any society [16,62]. We explored the impact of different behavioural response levels in rather a crude way, by modulating individuals' planning horizon and their risk sensitivity. Our model shows that behavioural responses based on long or short planning horizons do not minimize the outbreaks' sizes, since these bias the individual risk–benefit trade-offs. In these scenarios, the epidemiological dynamics produced resemble those expected without behavioural responses. Intermediate planning horizons minimize the outbreak sizes by adequately weighing the current and future expected utilities.

It is known that variations in the immune responses jointly acting with seasonal transmission generate a wide range of epidemic dynamics depending on the duration of the acquired immunity. It follows that the unfolding of subsequent outbreaks strongly depends on the underlying immunity landscapes. However, our results highlight the impact of sustained behavioural responses with low-risk acceptance (high-risk sensitivity), on equalizing the epidemic dynamics for scenarios where the underlying population's immunity profiles are highly different. This effect is driven by the modulation of behavioural responses according to the immunity acquired through the epidemic.

Here, we aim to understand the epidemiological consequences of adaptive human behaviour driven by risk perception and the associated population's immunity landscape on the multiple potential long-term dynamic and immunity scenarios. Our results emphasize the role of human behaviour on epidemic surveillance and highlight potential population scale effects driven by the interaction between the population's immunity landscape and the associated behavioural responses. Particularly, our results show that depending on the complexity of the population's immunity landscape and on the population's risk sensitivity, adaptive behavioural responses would avoid big outbreaks (produced due to the replenishment of the susceptible populations), and would induce uniform inter-epidemic periods (driven by the seasonal force of infection). Extensions of our baseline model incorporating information delay in the decision-making process show that behavioural-driven oscillatory dynamics are a potential outcome (see electronic supplementary material, appendix). This occurs when the risk–response trade-off produces appropriate feedback between the epidemic dynamics, information availability and risk sensitivity. Finally, we showed that accurate characterization of the population's behavioural responses during epidemics is intrinsically dependent on the individuals' immune life histories, which drive the population's immunity landscape. Particularly, in a wider health policy context, while adaptive responses are expected to occur during an epidemic, these behavioural decisions are driven by individual-level incentives, which partially depend on the potential health status.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. Google LLC 'Google COVID-19 Community Mobility Reports' is publicly available. Supplementary material is available online [63].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. B.E.: conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing—original draft, writing—review and editing; C.M.S.-R.: investigation, methodology, visualization, writing—original draft, writing—review and editing; B.T.G.: investigation, methodology, visualization, writing—original draft, writing—review and editing; S.A.L.: funding acquisition, investigation, methodology, visualization, writing—original draft, writing—review and editing; M.M.: conceptualization, funding acquisition, investigation, methodology, visualization, writing—original draft, writing—review and editing. All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interest declaration. We declare we have no competing interests.

Funding. This work was partially supported by the NSF through DMS Award no. 2327710 and DMS Award no. 2327711; Centers for Disease Control and Prevention (CDC) through Pathogen Genomics Centers of Excellence network (PGCoE) grant 6NU50CK000555-03-01; the Defense Threat Reduction Agency (DTRA) contract HDTRA120F0017; the National Science Foundation (NSF) through Expeditions in Computing Grant CCF-1918656 and CCF-1917819; Princeton Catalysis Initiative; Princeton Precision Health. C.M.S.-R. gratefully acknowledges funding from the Miller Institute for Basic Research in Science of UC Berkeley via a Miller Research Fellowship. B.T.G. acknowledges funding from Princeton Catalysis Initiative, Princeton Precision Health.

References

1. Espinoza B *et al*. 2023 Coupled models of genomic surveillance and evolving pandemics with applications for timely public health interventions. *Proc. Natl Acad. Sci. USA* **120**, e2305227120. (doi:10.1073/pnas.2305227120)

2. Saad-Roy CM *et al*. 2020 Immune life history, vaccination, and the dynamics of SARS-CoV-2 over the next 5 years. *Science* **370**, 811–818. (doi:10.1126/science.abd7343)
3. Kissler SM, Tedijanto C, Goldstein E, Grad YH, Lipsitch M. 2020 Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* **368**, 860–868. (doi:10.1126/science.abb5793)
4. Saad-Roy CM *et al*. 2021 Epidemiological and evolutionary considerations of SARS-CoV-2 vaccine dosing regimes. *Science* **372**, 363–370. (doi:10.1126/science.abg8663)
5. Wagner CE *et al*. 2021 Vaccine nationalism and the dynamics and control of SARS-CoV-2. *Science* **373**, eabj7364. (doi:10.1126/science.abj7364)
6. Saad-Roy CM, Morris SE, Baker RE, Farrar J, Graham AL, Levin SA, Wagner CE, Metcalf CJE, Grenfell BT. 2023 Medium-term scenarios of COVID-19 as a function of immune uncertainties and chronic disease. *J. R. Soc. Interface* **20**, 20230247. (doi:10.1098/rsif.2023.0247)
7. Grenfell BT, Pybus OG, Gog JR, Wood JLN, Daly JM, Mumford JA, Holmes EC. 2004 Unifying the epidemiological and evolutionary dynamics of pathogens. *Science* **303**, 327–332. (doi:10.1126/science.1090727)
8. Saad-Roy CM, Metcalf CJE, Grenfell BT. 2022 Immuno-epidemiology and the predictability of viral evolution. *Science* **376**, 1161–1162. (doi:10.1126/science.abn9410)
9. Bavel JJV *et al*. 2020 Using social and behavioural science to support COVID-19 pandemic response. *Nat. Hum. Behav.* **4**, 460–471. (doi:10.1038/s41562-020-0884-z)
10. Lucchini L, Centellegher S, Pappalardo L, Gallotti R, Privitera F, Lepri B, De Nadai M. 2021 Living in a pandemic: changes in mobility routines, social activity and adherence to COVID-19 protective measures. *Sci. Rep.* **11**, 24452. (doi:10.1038/s41598-021-04139-1)
11. Rahmandad H, Xu R, Ghaffarzadegan N. 2022 A missing behavioural feedback in COVID-19 models is the key to several puzzles. *BMJ Glob. Health* **7**, e010463. (doi:10.1136/bmjgh-2022-010463)
12. Lim TY, Xu R, Ruktanonchai N, Saucedo O, Childs LM, Jalali MS, Rahmandad H, Ghaffarzadegan N. 2023 Why similar policies resulted in different COVID-19 outcomes: how responsiveness and culture influenced mortality rates. *Health Aff.* **42**, 1637–1646. (doi:10.1377/hlthaff.2023.00713)
13. Chen J, Marathe A, Marathe M. 2018 Feedback between behavioral adaptations and disease dynamics. *Sci. Rep.* **8**, 12452. (doi:10.1038/s41598-018-30471-0)
14. Rahmandad H. 2022 Behavioral responses to risk promote vaccinating high-contact individuals first. *Syst. Dyn. Rev.* **38**, 246–263. (doi:10.1002/sdr.1714)
15. Levin SA, Milner HV, Perrings C. 2021 The dynamics of political polarization. *Proc. Natl Acad. Sci. USA* **118**, e2116950118. (doi:10.1073/pnas.2116950118)
16. Yang L, Constantino SM, Grenfell BT, Weber EU, Levin SA, Vasconcelos VV. 2022 Sociocultural determinants of global mask-wearing behavior. *Proc. Natl Acad. Sci. USA* **119**, e2213525119. (doi:10.1073/pnas.2213525119)
17. Wellenius GA *et al*. 2021 Impacts of social distancing policies on mobility and COVID-19 case growth in the US. *Nat. Commun.* **12**, 3118. (doi:10.1038/s41467-021-23404-5)
18. Petherick A, Goldszmidt R, Andrade EB, Furst R, Hale T, Pott A, Wood A. 2021 A worldwide assessment of changes in adherence to COVID-19 protective behaviours and hypothesized pandemic fatigue. *Nat. Hum. Behav.* **5**, 1145–1160. (doi:10.1038/s41562-021-01181-x)
19. Chen C *et al*. 2024 Wastewater-based epidemiology for covid-19 surveillance: a survey. *arXiv* 2403.15291v1.
20. Margevicius KJ *et al*. 2016 The biosurveillance analytics resource directory (BARD): facilitating the use of epidemiological models for infectious disease surveillance. *PLoS One* **11**, e0146600. (doi:10.1371/journal.pone.0146600)
21. Perry HN, McDonnell SM, Alemu W, Nsubuga P, Chungong S, Otten MW, Lusamba-dikassa PS, Thacker SB. 2007 Planning an integrated disease surveillance and response system: a matrix of skills and activities. *BMC Med.* **5**, 1–8. (doi:10.1186/1741-7015-5-24)
22. Wolfe CM *et al*. 2021 Systematic review of integrated disease surveillance and response (IDSR) implementation in the African region. *PLoS One* **16**, e0245457. (doi:10.1371/journal.pone.0245457)
23. Baker RE, Yang W, Vecchi GA, Metcalf CJE, Grenfell BT. 2020 Susceptible supply limits the role of climate in the early SARS-CoV-2 pandemic. *Science* **369**, 315–319. (doi:10.1126/science.abc2535)
24. Fenichel EP *et al*. 2011 Adaptive human behavior in epidemiological models. *Proc. Natl Acad. Sci. USA* **108**, 6306–6311. (doi:10.1073/pnas.1011250108)
25. Espinoza B, Marathe M, Swarup S, Thakur M. 2021 Asymptomatic individuals can increase the final epidemic size under adaptive human behavior. *Sci. Rep.* **11**, 19744. (doi:10.1038/s41598-021-98999-2)
26. Espinoza B, Swarup S, Barrett CL, Marathe M. 2022 Heterogeneous adaptive behavioral responses may increase epidemic burden. *Sci. Rep.* **12**, 11276. (doi:10.1038/s41598-022-15444-8)
27. Jackson MO, Rogers BW, Zenou Y. 2017 The economic consequences of social-network structure. *J. Econ. Lit.* **55**, 49–95. (doi:10.1257/jel.20150694)
28. Granovetter M. 2005 The impact of social structure on economic outcomes. *J. Econ. Perspect.* **19**, 33–50. (doi:10.1257/0895330053147958)
29. Campos-Mercade P, Meier AN, Schneider FH, Meier S, Pope D, Wengström E. 2021 Monetary incentives increase COVID-19 vaccinations. *Science* **374**, 879–882. (doi:10.1126/science.abm0475)
30. Verity R *et al*. 2020 Estimates of the severity of coronavirus disease 2019: a model-based analysis. *Lancet Infect. Dis.* **20**, 669–677. (doi:10.1016/S1473-3099(20)30243-7)
31. Espinoza B, Castillo-Chavez C, Perrings C. 2020 Mobility restrictions for the control of epidemics: when do they work? *PLoS One* **15**, e0235731. (doi:10.1371/journal.pone.0235731)
32. Chang S, Pierson E, Koh PW, Gerardin J, Redbird B, Grusky D, Leskovec J. 2021 Mobility network models of COVID-19 explain inequities and inform reopening. *Nature* **589**, 82–87. (doi:10.1038/s41586-020-2923-3)
33. Davies NG, Klepac P, Liu Y, Prem K, Jit M, CMMID COVID-19 working group, Eggo RM. 2020 Age-dependent effects in the transmission and control of COVID-19 epidemics. *Nat. Med.* **26**, 1205–1211. (doi:10.1038/s41591-020-0962-9)
34. Dowd JB, Andriano L, Brazel DM, Rotondi V, Block P, Ding X, Liu Y, Mills MC. 2020 Demographic science aids in understanding the spread and fatality rates of COVID-19. *Proc. Natl Acad. Sci. USA* **117**, 9696–9698. (doi:10.1073/pnas.2004911117)
35. Jeyanathan M, Afkhami S, Smaill F, Miller MS, Lichty BD, Xing Z. 2020 Immunological considerations for COVID-19 vaccine strategies. *Nat. Rev. Immunol.* **20**, 615–632. (doi:10.1038/s41577-020-00434-6)
36. Althouse BM, Wenger EA, Miller JC, Scarpino SV, Allard A, Hébert-Dufresne L, Hu H. 2020 Superspreading events in the transmission dynamics of SARS-CoV-2: opportunities for interventions and control. *PLoS Biol.* **18**, e3000897. (doi:10.1371/journal.pbio.3000897)
37. Dixit AK, Espinoza B, Qiu Z, Vullikanti A, Marathe MV. 2023 Airborne disease transmission during indoor gatherings over multiple time scales: modeling framework and policy implications. *Proc. Natl. Acad. Sci. U.S.A* **120**, e2216948120. (doi:10.1073/pnas.2216948120)
38. Laxminarayan R, Wahl B, Dudala SR, Gopal K, Mohan B C, Neelima S, Jawahar Reddy KS, Radhakrishnan J, Lewnard JA. 2020 Epidemiology and transmission dynamics of COVID-19 in two Indian states. *Science* **370**, 691–697. (doi:10.1126/science.abd7672)
39. Callaway E. 2021 Fast-spreading COVID variant can elude immune responses. *Nature* **589**, 500–501. (doi:10.1038/d41586-021-00121-z)
40. Tregoning JS, Flight KE, Higham SL, Wang Z, Pierce BF. 2021 Progress of the COVID-19 vaccine effort: viruses, vaccines and variants versus efficacy, effectiveness and escape. *Nat. Rev. Immunol.* **21**, 626–636. (doi:10.1038/s41577-021-00592-1)

41. Qiu Z *et al*. 2022 Understanding the coevolution of mask wearing and epidemics: a network perspective. *Proc. Natl Acad. Sci. USA* **119**, e2123355119. (doi:10.1073/pnas.2123355119)
42. Machingaidze S, Wiysonge CS. 2021 Understanding COVID-19 vaccine hesitancy. *Nat. Med.* **27**, 1338–1339. (doi:10.1038/s41591-021-01459-7)
43. Prieto Curiel R, González Ramírez H. 2021 Vaccination strategies against COVID-19 and the diffusion of anti-vaccination views. *Sci. Rep.* **11**, 6626. (doi:10.1038/s41598-021-85555-1)
44. Kuhlman CJ, Marathe A, Vullikanti A, Halim N, Mozumder P. 2022 Natural disaster evacuation modeling: the dichotomy of fear of crime and social influence. *Soc. Netw. Anal. Min.* **12**, 1–18. (doi:10.1007/s13278-021-00839-8)
45. Bauch CT. 2005 Imitation dynamics predict vaccinating behaviour. *Proc. R. Soc. B Biol. Sci.* **272**, 1669–1675. (doi:10.1098/rspb.2005.3153)
46. Traulsen A, Levin SA, Saad-Roy CM. 2023 Individual costs and societal benefits of interventions during the COVID-19 pandemic. *Proc. Natl Acad. Sci USA* **120**, e2303546120. (doi:10.1073/pnas.2303546120)
47. Saad-Roy CM, Traulsen A. 2023 Dynamics in a behavioral-epidemiological model for individual adherence to a nonpharmaceutical intervention. *Proc. Natl Acad. Sci. USA* **120**, e2311584120. (doi:10.1073/pnas.2311584120)
48. Chen X, Fu F. 2019 Imperfect vaccine and hysteresis. *Proc. R. Soc. B* **286**, 20182406. (doi:10.1098/rspb.2018.2406)
49. Glaubitz A, Fu F. 2020 Oscillatory dynamics in the dilemma of social distancing. *Proc. R. Soc. A.* **476**, 20200686. (doi:10.1098/rspa.2020.0686)
50. Bauch CT, Galvani AP. 2013 Social factors in epidemiology. *Science* **342**, 47–49. (doi:10.1126/science.1244492)
51. De Domenico M, Altmann EG. 2020 Unraveling the origin of social bursts in collective attention. *Sci. Rep.* **10**, 4629. (doi:10.1038/s41598-020-61523-z)
52. Gallotti R, Valle F, Castaldo N, Sacco P, De Domenico M. 2020 Assessing the risks of 'infodemics' in response to COVID-19 epidemics. *Nat. Hum. Behav.* **4**, 1285–1293. (doi:10.1038/s41562-020-00994-6)
53. Towers S *et al*. 2015 Mass media and the contagion of fear: the case of Ebola in america. *PLoS One* **10**, e0129179. (doi:10.1371/journal.pone.0129179)
54. Vosoughi S, Roy D, Aral S. 2018 The spread of true and false news online. *Science* **359**, 1146–1151. (doi:10.1126/science.aap9559)
55. Barrett C, Bisset K, Leidig J, Marathe A, Marathe MV. 2010 An integrated modeling environment to study the coevolution of networks, individual behavior, and epidemics. *AI Mag.* **31**, 75–87. (doi:10.1609/aimag.v31i1.2283)
56. Bitler M, Hoynes H, Schanzenbach DW. 2020 Why the safety net might not respond as effectively to COVID-19 as it should. *Milbank Quarterly Opinion*. 30 April 2020. (doi:10.1599/mqop.2020.0401)
57. Weill JA, Stigler M, Deschenes O, Springborn MR. 2020 Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proc. Natl Acad. Sci. USA* **117**, 19658–19660. (doi:10.1073/pnas.2009412117)
58. Yesuf M, Bluffstone RA. 2009 Poverty, risk aversion, and path dependence in low-income countries: experimental evidence from Ethiopia. *Am. J. Agric. Econ.* **91**, 1022–1037. (doi:10.1111/j.1467-8276.2009.01307.x)
59. Kluwe-Schiavon B, Viola TW, Bandinelli LP, Castro SCC, Kristensen CH, Costa da Costa J, Grassi-Oliveira R. 2021 A behavioral economic risk aversion experiment in the context of the COVID-19 pandemic. *PLoS One* **16**, e0245261. (doi:10.1371/journal.pone.0245261)
60. Moore CA, Ruisch BC, Granados Samayoa JA, Boggs ST, Ladanyi JT, Fazio RH. 2021 Contracting COVID-19: a longitudinal investigation of the impact of beliefs and knowledge. *Sci. Rep.* **11**, 20460. (doi:10.1038/s41598-021-99981-8)
61. Singh M, Marathe A, Marathe MV, Swarup S. 2018 Behavior model calibration for epidemic simulations. *Proc. Int. Joint Conf. Auton. Agents Multiagent Syst.* **2018**, 1640–1648.
62. Moya C, Cruz Y Celis Peniche P, Kline MA, Smaldino PE. 2020 Dynamics of behavior change in the COVID world. *Am. J. Hum. Biol.* **32**, e23485. (doi:10.1002/ajhb.23485)
63. Espinoza B, Saad-Roy C, Grenfell BT, Levin S, Marathe M. 2024 Supplementary material from: Adaptive human behavior modulates the impact of immune life history and vaccination on long-term pandemic dynamics. Figshare (doi:10.6084/m9.figshare.c.7481230)