Behavioral responses to risk promote vaccinating high-contact individuals first

Hazhir Rahmandad *

Abstract
How should communities prioritize COVID-19 vaccinations? Prior studies found that prioritizing the elderly and most vulnerable minimizes deaths. However, prior research has ignored how behavioral responses to risk of disease endogenously change transmission rates. We show that incorporating risk-driven behavioral responses enhances fit to data and may change prioritization to vaccinating high-contact individuals. Behavioral responses matter because deaths grow exponentially until communities are compelled to reduce contacts, with deaths stabilizing at levels that oblige higher-contact groups to sufficiently cut their interactions and slow transmissions. More lives may be saved by vaccinating and taking those high-contact groups out of transmission chains earlier because the remaining groups will take more precautions while waiting for their turn for vaccination. These findings are especially important considering the need for further vaccination in many countries, the emergence of new variants, and the expected challenge of distributing new vaccines in the coming months and years.

Introduction
Rapid development of effective vaccines has been one of the bright spots in tackling COVID-19, one of the most disruptive global challenges in the recent history. Yet, beyond the initial development, the production and effective distribution of vaccines remains an ongoing challenge. For example, by late March 2022, some 16 months since the start of vaccine administration, more than half the population remains without full vaccination in 86 countries, mostly among the low-income nations (based on the OWID portal by Mathieu et al., 2021). The challenge is likely to remain relevant: new variants of COVID-19, such as Omicron, will continue to evolve to bypass vaccine protection, requiring new vaccines and ongoing vaccine administration. Beyond COVID-19, prioritizing vaccination against emerging diseases is an important and recurring problem.
The distribution of vaccines with limited supply or distribution capacity raises the question of prioritization (Lipsitch and Dean, 2020; Fitzpatrick and Galvani, 2021): who should be first vaccinated to minimize the burden of the disease? Prioritizing different groups can be justified by focusing on different mechanisms: healthcare workers are more exposed to the disease and their absence is costlier when a wave of the epidemic hits (Buckner et al., 2021); THE elderly have much higher risk of death should they contract COVID-19 (Levin et al., 2020); and the younger groups may be more important conduits of transmission (Rumain et al., 2021). More subtle mechanisms may also be at play. On the one hand, some groups (e.g. elderly) may be more responsive to the risk of the disease, bringing down their interactions and protecting themselves when risks increase (Masters et al., 2020). On the other hand, some groups may ignore Non-Pharmaceutical Interventions (NPIs) out of necessity or lack of concern, keep high levels of interactions, spread the disease, and contribute to deaths as long as ongoing risks are tolerable to them. Therefore, taking the latter group out of transmission chains through vaccination could slow down deaths across the population, leading to significant indirect benefits (Gallagher et al., 2021).

Determining which of these mechanisms is more important requires quantitative analysis. Several researchers have addressed this question in the context of COVID-19 with different modeling approaches. Some have used statistical methods that consider the direct protective benefits of vaccine for different population groups, and they aggregate those benefits to assess alternative prioritzations based on age (Goldstein et al., 2021) or geography (Wrigley-Field et al., 2021). The drawback of these methods is that they ignore the interactions among groups, missing various indirect benefits of vaccines (Gallagher et al., 2021). Accounting for interdependencies, researchers can model the progression of epidemic in a population consisting of different subgroups (e.g. different ages or occupations) and assess how prioritizing each subgroup in vaccination changes the total number of infections and deaths. Using this approach, Buckner et al. (2021) recommend prioritizing essential workers, followed by the elderly. Jentsch et al. (2021) find that in the Canadian context prioritizing the elderly minimizes deaths. Moore et al. (2021) also find similar results, promoting the vaccination of elderly and healthcare workers first. In one of the most comprehensive studies in this space Bubar et al. (2021) (BL for shorthand) support vaccinating the elderly first to minimize total deaths and years of life lost (YLL). Their results are robust as long as COVID-19’s basic reproduction number ($R_0$; the number of secondary infections from an index case in a fully susceptible population who is not adopting any NPIs) is above 1.4 in the simulations, although such prioritization may lead to more cases. Their analysis incorporates age-specific contact and fatality patterns, and vaccine effectiveness and hesitancy, offering a nuanced view of vaccine prioritization under various contingencies.
Overall, prior studies consistently point to prioritizing the elderly (often after critical-care workforce) for vaccination. With the elderly’s Infection Fatality Rate (IFR) orders of magnitude higher than the young age cohort’s IFR (Levin et al., 2020), the results are also intuitive. In fact, this recommendation has been adopted across many countries. Yet, the analysis in all prior studies is missing a key factor in COVID-19 dynamics: that in response to perceived risks people and governments change their behaviors, policies, and nonpharmaceutical interventions, altering transmission rates endogenously (Bagnoli et al., 2007; Funk et al., 2010). We call this feedback mechanism “behavioral response” and make it the focus of our study while acknowledging that many other behavioral aspects are potentially relevant but not discussed here. A detailed review of the models in prior work show that only one (Jentsch et al., 2021) partially includes an endogenous behavioral-response function and most others, including BL, ignore the feedback between risk perception and changes in behavior. However, such behavioral responses to changing risk perceptions matter (Funk et al., 2010). For example, they explain why despite initial $R_0$ estimates much higher than one (Alimohamadi et al., 2020) few countries have been overrun by the disease. After an initial wave, those behavioral responses reduced contacts enough for cases to oscillate around a steady flow. In effect, most communities converge to effective reproduction numbers ($R_e$) around one (Lim and Rahmandad, 2022), otherwise cases and deaths grow exponentially. Behavioral responses are also needed to explain the multiple waves of the epidemic (emerging from delays in risk perception, relaxation of perceived risk key, and changes in behaviors; all part of the behavioral-response balancing loop) (Struben, 2020), and orders of magnitude variation in cases and deaths across nations (Lim and Rahmandad, 2022). Behavioral responses are also key for models that provide reliable future projections (Eksin et al., 2019; Perrings et al., 2014; Rahmandad et al., 2022).

While prior work has started to account for behavioral feedbacks in some settings (Funk et al., 2010), the impact of this feedback loop on vaccination priority is less known, but potentially important. For example, reducing deaths through vaccination leads to relaxation of risks and a rebound in cases and deaths. This rebound can change the calculus: first vaccinating population groups with more contacts, or those less responsive to risk, may better leverage the caution of more responsive groups who would remain vigilant and limit deaths until they are vaccinated. On the other hand, deprioritizing high-contact groups means the rebound effect will be especially strong for them: seeing the early benefits of vaccines in reducing deaths (by protecting the elderly), they increase interactions more, keeping reproduction number high and the disease circulating for longer and all the while increasing deaths. However, it is not clear if such mechanisms may change the overall policy recommendations. In this article, we analyze how behavioral responses impact the overall calculus of vaccination priority.
**Methods**

To build on prior work and make results directly comparable with past findings, we start with the model introduced by BL, use the same parameterizations, and only extend the model to potentially account for behavioral responses to risk as an endogenous feedback loop. Figure 1 summarizes the model’s stock-and-flow structure and several equations. This model follows an SEIR (Susceptible, Exposed, Infectious, Removed) framework, separating population groups based on their vaccination status (subscript v denotes vaccinated; subscript x denotes people who are “vaccine hesitant,” i.e. not accepting vaccination; $h_{frac}$ is a parameter that sets vaccine hesitancy level) as well as age (nine age groups: 0–10, 10–20, ..., 80+). The model does not account for testing or hospitalization, emergence of new variants, loss of immunity, or heterogeneity in population beyond age groups. These assumptions, while consistent with BL’s model and helpful for establishing simple, clear baselines and limit the extrapolation of results to some practical problems. Our focus here is thus on identifying key mechanisms and developing basic intuitions; concrete policy guidance would require more careful matching of model assumptions to the policy problem at hand.

In the diagram, the vaccine administration rate to susceptible population is $z$ (note that all variables are subscripted for age groups). Vaccine effectiveness has three distinct components: in avoiding infection in the vaccinated person, $v_e$ ($=0.9$ in baseline); effectiveness in reducing infectivity of a vaccinated (but infected) person to others, $v_{ei}$ ($=1$; i.e. vaccinated do not infect others); and effectiveness in reducing infection fatality rate of a vaccinated person should they contact the disease, $v_{ed}$ ($=0.1$ in baseline). In setting the baseline model parameters, we follow BL’s assumptions but conduct

![Fig. 1](image_url). The overview of the model. Stock-and-flow structure is shown along with the key behavioral feedback loop (but much else is removed for clarity). The simplified flow formulations use the following convention: the equation on each flow represents the fractional outflow from the source stock, e.g. the $\lambda g$ on the flow from S to E means the actual equation is $S \lambda g$. Abbreviations (for items not discussed in the text): S = Susceptible; E = Exposed; I = Infectious; R = Recovered; D = Dead; Subscripts: v for vaccinated; x for vaccine hesitant [Color figure can be viewed at wileyonlinelibrary.com]
sensitivity analysis to inform robustness. The force of infection, $\lambda$, captures both the frequency of contacts and the risk of transmission (detailed below). $t_E$ (=3 days) and $t_I$ (=5 days) represent duration of incubation and infectious periods, and $f$ is the Infection Fatality Rate (IFR). $f$ varies by age groups, from 1e-5 (for 0–10 age) to 0.15 (for 80+) (Levin et al., 2020), and is parameterized by BL based on the earlier variants of the SARS-CoV-2 virus.

The key extension of the model in this study is to account for the behavioral-response feedback loop(s) that connect perceived recent deaths ($d^r$) to the transmission rate through a response function ($g$; Eq. (3)). Specifically, we formulate the force of infection for age group $i$ as:

$$\lambda_i = \beta u_i \sum_j c_{ij} \frac{m_j}{N_j - D_j} w^\delta; \quad (1)$$

$$m_j = (I_j + I_{sj}) g_j + I_{vj} (1 - v_{ei}) (1 - (1 - g_j) v_g). \quad (2)$$

$\beta$ is a parameter representing the baseline transmission rate (same for all age groups), $u_i$ is the age specific susceptibility to infection conditional on a contagious contact (varying between 0.4 and 0.88 for different age groups (Davies, Klepac et al., 2020)), and $c_{ij}$ is the average daily contact rate between a person in age group $i$ and those in group $j$ (adopted from prepandemic estimates (Prem, Zandvoort et al., 2021) following BL). $m_j$ (Eq. (2)) is the infectious population of age-group $j$, weighted by their behavioral responses, and accounts for the number of infectious people in each age and vaccination group, as well as their potential reductions in risky contacts due to the behavioral response ($g$). $m_j$ multiplied by $c_{ij}$ and divided by the total population alive in that group ($N_j - D_j$; where $N_j$ is the total initial population in group $j$ and $D_j$ the cumulative deaths) provides an estimate for the number of potentially infectious contacts between groups $i$ and $j$. Finally, $w$ captures impact of seasonality on transmission rates and is adopted from year-round values for the United States by Xu et al. (2021) and weighted by a parameter $\delta$ that we estimate. Assuming $g = 0$ and $w = 1$ will simplify these transmission equations to those used by BL.

Finally, the response function, $g$, is the reduction in risky contacts by a population group. This function appears both in how much each susceptible group exposes itself to interactions (e.g. the $g$ in $S\lambda g$ flow from $S$ to $I$) and how much the infected groups contribute to the force of infection (in equation for $m_j$). Note that we include the possibility that vaccinated people stop using NPIs, and parameter $v_g$ (=0 in baseline) controls their responsiveness. The response to risk is formulated as:

$$g_j = \exp \frac{d}{\delta}. \quad (3)$$
Here \( d' \) is a first order delay of per capita death rate (\( d \): daily death rate summed across all population groups and normalized by total population) with an asymmetric delay length, allowing different speeds in the ramp up versus relaxation of risks. Parameter \( \alpha \) sets the threshold of recent deaths that elicits the behavioral responses and with large enough values, negates such responses. We note that deaths are not the only signal of the risk, and others, from hospitalizations to infections, may play a role in practice. Our formulation is empirically consistent with other work that finds recent death signals offer better predictive models of pandemic (Rahmandad et al., 2022) and theoretically plausible due to the saliency of death (and its close correlation with other signals such as hospitalization).

Following prior work (Rahmandad et al., 2021), we calibrate the model to the U.S. data, matching weekly COVID-19 deaths for each age group to the corresponding data series from the United States for the year 2020, using a negative binomial likelihood function to account for fat tails and autocorrelation. We estimate the following six model parameters. Three apply to both BL model and the modified version with behavioral response: baseline transmission rate (\( \beta \)), strength of seasonality effect (\( \delta \)), and the fraction of population initially infected (to match the start point of the pandemic). Another three are needed to capture the behavioral response: two lag times for upward (\( \tau_u \)) and downward (\( \tau_d \)) risk adjustment, as well as the daily (per capita) death rates eliciting notable behavioral change (\( \alpha \)). In baseline analysis, we assume the same \( \alpha \) for all age groups but consider a scenario where older groups are more responsive to risk in the robustness section.

The analysis consists of two steps. We first calibrate both the BL model (without behavioral response) and the extension that includes the behavioral response, to U.S. data (note that BL do not report results from any calibration; rather they analyze sensitivity to different \( R_0 \) values). Comparing the quality of fit between the two informs the importance of incorporating the behavioral responses for understanding the historical behaviors. Then, using the calibrated model parameters, we introduce vaccination in the model starting from January 2021 and continue with a fixed rate that ensures the interested population is covered over a given vaccination periods. We compare the results from both models (with and without behavioral feedback) under two competing prioritization schemes: (a) Elderly-first: we give the highest priority to the 80+, going down in priority by age group, and (b) High-contact-First: we give the higher priority to those with higher daily contacts. Specifically total contacts are: \( C_i = \sum_j c_{ij} \) = [14, 23, 16, 17, 16, 13, 10, 6, 6] (contacts per day) for the different age groups. This implies 10–20 year olds will first get vaccinated, followed by 30–40, 20–30, 40–50, and so on. These prioritizations are only two options among many possibilities. We chose these for their simplicity, their application in
prior research, and the fact that the comparison informs how the behavioral feedback may change the outcomes across a broader set of prioritizations schemes.

Our primary outcome measure is the cumulative number of deaths due to COVID-19. The focus on deaths is consistent with prior work (Buckner et al., 2021; Gallagher et al., 2021; Moore et al., 2021), and while other outcomes may be relevant, they are either highly correlated with the deaths (e.g. hospitalizations), or less important policy-wise (e.g. cases). For the baseline analysis, we also report the Years of Life Lost (YLL) and changes in interactions, a proxy for economic impact. Total deaths (cumulative from the beginning of 2021) count every death with the same weight, while the YLL gives more weight to deaths among the younger age groups based on their longer life expectancy (WHO, 2020). For example, a death in the 0–10 years-old group creates 76.8 years of YLL, compared to 7.6 year when an 80+ person dies from COVID-19. In our simulations, dynamics end by mid-2022 as this model does not include loss of immunity and new variants (Table 1).

**Results**

Calibrating the BL model to prevaccination death rates in the United States requires an $R_0$ that peaks as low as 1.3 and still offers an unsatisfactory fit (Figure 2a). The simple extension that incorporates behavioral responses by scaling contact rates by a factor $g(t) = \exp^{-d(t)/\alpha}$ matches the waves of pandemic across age groups (Panel B) with $R_0$ peaking at the more realistic value of 3.8. The $R^{2}$ and Mean Absolute Error Normalized by Mean (MAEN) measures of fit are respectively 0.091 and 73 percent for the BL model without behavioral feedback, but improve to 0.54 and 41 percent when this feedback is included. Perceived risk, $d'(t)$, is estimated to adjust

| Table 1. Model parameters and assumptions. Vaccination assumptions are in the left columns and estimated parameters on the right |
|---|---|---|
| Vaccination Assumptions | Value (source) | Parameter (estimated) | Estimates (with/without response) |
| $v_e$: Vaccine effectiveness against transmission | 0.9 (BL) | $\beta$: Baseline Transmission Rate | 0.093/0.030 |
| $\nu_{ei}$: Effectiveness against infectivity of vaccinated but infected | 1 (BL) | $\delta$: Seasonality Effect | 3.3/2.0 |
| $\nu_{ed}$: Vaccine effectiveness against deaths | 0.1 (BL) | $\alpha$: Response threshold | 8.7 deaths/million/day |
| $\nu_v$: Responsiveness of vaccinated to risk | 0 (Assumption) | $\tau_u$: Upward risk adjustment time | 7.5 days |
| $h_{fc}$: Fraction vaccine hesitant | 0.3 (BL) | $\tau_d$: Downward risk adjustment time | 46 days |

© 2022 The Author. *System Dynamics Review* published by John Wiley & Sons Ltd on behalf of System Dynamics Society. DOI: 10.1002/sdr
faster when deaths are growing (estimated lag: 7.5 days) than when deaths subside (estimated lag: 46 days). The risk level compelling significant contact reductions \(\alpha\) is estimated to be 8.7 deaths/million/day.

Behavioral response feedback, which is absent from BL and most other vaccination analyses (Buckner et al., 2021; Gallagher et al., 2021; Moore et al., 2021), changes both the trajectory of deaths and the vaccination priorities. Figure 3 compares alternative prioritization schemes using the calibrated BL model (panels a and c) and its extension “With Behavioral Response” (panels b and d). In these scenarios, and following BL’s baseline, we assume that vaccination is effective against transmission but not deaths \(\nu = 0.9, \nu_{ei} = 1, \text{and } \nu_{ed} = 0; \text{see robustness below}\) and a vaccine-hesitant population fraction of \(h_{fc} = 0.3\). Consistent with BL findings Elderly-First policy is best when behavioral response is ignored. The cumulative deaths and YLLs postvaccination are always lower for the Elderly-First (solid lines in Figure 3) compared to the High-Contact-First policies (Panel A) regardless of how short the vaccination period is. On the other hand, incorporating behavioral-response feedback flips the priority for any vaccination rollout that takes more than 6 months. For vaccination periods above 130 days, the High-Contact-First policy dominates in terms of YLL outcome while the policy reversal point is at 180 days if one uses total deaths as the main outcome (Figure 3b). The magnitude of the impact is considerable: in 2021 under the calibrated BL model, vaccinating the population over 250 days leads to 138 versus 203,000 deaths for Elderly-First and High-Contact-First policies respectively (Figure 3a). Figure 3c,d show the time trajectory of deaths and the reproduction number with (panel c) and without (panel d) behavioral response when vaccination is unfolding over 250 days (corresponding to the dashed vertical line in panels a and b). Figure 4 panel a shows the ratio of cumulative deaths under the two prioritization schemes with a similar
vertical line that corresponds to the simulated scenarios in Figure 3c,d. Thus the solid line (for no behavioral response) in Figure 4a shows a ratio of 138/203 = 0.68 at the intersection of vertical dashed line. The corresponding projections accounting for behavioral responses change to 116 and 101,000 deaths for Elderly-First and High-Contact-First policies respectively (ratio of 1.15; Figure 3b and dashed line on Figure 4a). Two observations require further explanation: First, deaths are higher without behavioral response.
Fig. 4. Summary of results and robustness checks. Each panel shows the ratio of Cumulative deaths under Elderly-First divided by High-Contact-First vaccine prioritization and graphed for different vaccination durations (inverse of speed). A number above 1 means High-Contact-First is better and below 1 puts Elderly-First on the top. Solid lines are for the model without behavioral response; Dashed lines for those including the effect. (a) Baseline (b) Changing vaccine effectiveness against deaths from 0.1 to 0.9 (c) Changing vaccine effectiveness against infecting others from 1 to 0.1 (d) Changing vaccine effectiveness against transmission from 0.9 to 0.5 (e) Assuming vaccinated individuals reduce contacts in response to risk (f) Changing vaccine hesitency from 0.3 to 0.1 (g) Assuming vaccine hesitency is lower for elderly (h) Assuming responsiveness to risk increases with age (i) and (j) Two combinations of alternative parameters. [Color figure can be viewed at wileyonlinelibrary.com]
Second, the ordering of the two vaccination policies change: the BL model suggests Elderly-First is better; adding behavioral response promotes the High-Contact-First. The large difference in deaths is partly due to the timing of projected epidemic waves. An $R_0$ of 1.3 estimated for BL model (which due to absence of behavioral feedbacks is much smaller than other estimates; Hao et al., 2020), plus the increased transmission with winter, means that absent behavioral responses $R_e$ would remain higher than 1 in early 2021, leading to a very large wave in the United States that infects many people before vaccination and raises deaths significantly before vaccination can curb the pandemic (Figure 3c). The large benefit of vaccinating elderly first (relative to High-Contact-First) in the BL model is partly due to removal of those with highest IFR in time for this major wave. In this scenario, the epidemic ends faster, because few people remain susceptible by April 2021 (due to the huge wave in early 2021 that depletes the susceptible population stock). With behavioral response, this early wave is endogenously brought under control because of the increased NPIs in response to the deaths in late 2020/early 2021. Thus, with behavioral response, deaths go down across both vaccination policies in the absence of the larger wave. On the other hand, with behavioral response, the epidemic lingers for longer due to a rebound effect: reduced deaths (due to vaccinations) increase interactions and allow for the disease to circulate for longer until enough of the population is vaccinated (or contracts the disease) (Figure 3d).

Two competing mechanisms explain why the preferred prioritization switches with the inclusion of behavioral response. First, vaccinating groups based on their IFR reduces deaths among the infected, promoting Elderly-First policy as prior research, and commonsense, recommends. The second mechanism operates through a subtler pathway which we call “controlling deaths through behavioral response.” When people change their behaviors in response to risk, ongoing deaths are determined largely by how responsive to risk different groups in a society are. Deaths stabilize at levels that compel enough precautions and NPIs to curtail the exponential growth of the epidemic, i.e. keep $R_{e-1}$ (Lim and Rahmandad, 2022). Bringing down the contacts of high-contact groups enough to reach $R_{e-1}$ would require much higher risk levels (i.e. observed death rates) compared to risk levels compelling sufficient reductions of interactions among low-contact elderly. In essence, before the epidemic loses momentum (due to herd immunity), the observed death rates are a function of how much risk (i.e. “deaths”) the (unvaccinated) population are willing to tolerate without changing their interactions substantially. Thus, ongoing deaths could be brought down further by first vaccinating those with higher contact rates (i.e. the High-Contact-First policy). Otherwise, these groups will continue to contribute to transmissions by ignoring NPIs until they are compelled to comply to NPIs by seeing higher death rates. Taking these groups out of transmission brings
down deaths by leaving in the transmission dynamics only those more responsive who will adopt NPIs more easily because they do not tolerate high death rates.

These two mechanisms compete to determine the effective vaccine prioritization scheme. Initially, the first mechanism brings down deaths faster under the Elderly-First policy (Figure 3d). However, due to the second mechanism, the remaining high-contact individuals keep the reproduction number higher under Elderly-First prioritization (than under High-Contact-First), increasing infections and later, deaths. The relative importance of these mechanisms depends on how fast vaccination is completed: if administered very quickly (under 180 days if one uses cumulative deaths as outcome; Figure 3b), there is not much time for the second mechanism to have an impact, and thus the Elderly-First strategy dominates. Otherwise, the second mechanism is strong enough to change the overall conclusion, as it does in the simulations in Figure 3d. As one may expect, the reversal of optimal policy is even more pronounced for YLL (Figure 3b) which happens as long as vaccination takes more than 130 days.

A separate trade-off related to interactions in the community is also noteworthy. The Elderly-First policy allows for a quick increase in the level of interactions in the society, because it more sharply brings down death rates (See Figure 3d, the solid black line initially going above the dashed one); however, the extension of the epidemic for longer in the Elderly-First prioritization leads to longer-term negative impacts on the magnitude of interactions in the society. As a result, the High-Contact-First policy dominates the Elderly-First both in terms of life savings and earlier return to higher levels of social and economic interactions.

In practice, these long-term projections (based only on 2020 data) proved optimistic: among others, the model did not anticipate the emergence of new dominant and more transmissive variants, including Delta and Omicron, and the resulting changes in transmission rates, fatality rates, and vaccine effectiveness (e.g. reducing $v_e$). Also, the BL assumptions on vaccine effectiveness proved less inaccurate: $v_{ei} = 1$ is too optimistic, and $v_{ed} = 0$ is too pessimistic. In fact, vaccines have proven to be very protective against deaths (Bernal et al., 2021; Liang et al., 2021). We therefore assess the robustness of results to these and a number of other considerations in Figure 4. In each panel, we show the ratio of cumulative deaths under Elderly-First vs. High-Contact-First policies, without (solid) and with (dashed) behavioral response and for different vaccination durations (X-axis). Whereas Panel a summarizes the baseline analysis, panels b–d show that results are robust to higher vaccine effectiveness against deaths (panel b), lower effectiveness against transmission of disease by the vaccinated (c), or limited protection against transmission of disease (d). In fact, lower transmission protection ($v_e = 0.5$) further weakens the Elderly-First strategy: in the absence of transmission protection, more elderly individuals suffer the risk of contagion and
death when the high-contact groups continue interacting without proper NPIs during the vaccination period. Panel E shows robustness to assuming that the vaccinated remain responsive to risk ($v_g = 1$). Reducing vaccine hesitancy ($h_{frac}$) from 30 to 10 percent also has little impact on the results (F), nor those making vaccine hesitancy a function of age (Panel G, where we assume hesitancy goes down with age, from 47 percent for 0–10 year-olds to 7 percent for 80+).

Panel H introduces the possibility that responsiveness to risk ($\alpha$) may change by age. Specifically, we reestimate the model with behavioral response allowing $\alpha$ to change linearly with age group (adding one free parameter to the model). The resulting fit improves slightly ($R^2 = 0.55$ and MAEN = 39 percent), and estimates show responsiveness is higher ($\alpha$ is smaller) for the older groups. Accounting for that dependency further strengthens preference for the High-Contact-First policy: while waiting for vaccination, the younger groups now increase death rates both because they have higher baseline contacts and because they are less responsive, tolerating higher death rates before the risks compel them to adopt the NPIs.

Importantly, while single parameter changes do not change the basic trends, results could qualitatively change under plausible combinations of alternative parameters. One such mix of parameters is shown in Panel I, where we assume vaccine is protective against death ($v_{ed} = 0.9$) but mildly effective against transmission ($v_a = 0.5$) and ineffective against infectivity ($v_{ei} = 0.1$). Such a vaccine does little to remove the vaccinated from transmission dynamics: they continue to be infected and infect others. In fact, if after vaccination they cease to be responsive to risk ($v_g = 0$; as we assume), vaccinating the High-Contact-First will be counterproductive because those vaccinated early on remain in transmission chains and even more actively contribute to increased death rates. The exact parameters matter in such scenarios; e.g. in Panel J, we show that a modest increase in infectivity protection of vaccine ($v_{ei} = 0.7$) can restore the preference for the High-Contact-First scheme.

Overall, the strength of the mechanism “controlling deaths through behavioral response,” and thus the optimal prioritization, revolves around two questions: (i) does vaccination remove the vaccinated from transmission chains (either by protecting them, or by reducing their infectivity), and (ii) are vaccines protective against deaths? A vaccine that does neither is useless regardless of prioritization. One that reduces deaths without removing the vaccinated from transmission dynamics should be prioritized based on Elderly-First (in fact such a vaccine is better seen as a prophylactic treatment). One that removes the vaccinated from transmission (regardless of impact on deaths) is better prioritized based on contact rates (and/or lack of responsiveness). Note that controlling deaths through a behavioral-response mechanism would be even stronger if the less responsive groups (i.e. those requiring much higher death rates to be convinced of the risks) could be
vaccinated first. For simplicity, we did not explore such alternative prioritization schemes here, but they remain important for optimization of prioritizations in specific applications.

**Discussion**

Behavioral responses, missing from existing analyses of vaccination priority, are not only needed for understanding the observed and future trajectories of the pandemic but also shift the optimal vaccination policy significantly in favor of prioritizing high-contact groups first. This finding is robust as long as vaccines protect against the transmission of the disease and vaccination does not happen very quickly. It also is robust to accounting for outcomes beyond death rates, including YLL and the level of interactions in the community (a proxy for economic costs). The magnitude of the impact is not trivial: changing prioritization from Elderly-First to High-Contact-First reduced deaths by more than 14 percent (~15,000) in the baseline simulations, with even larger impacts on YLL.

Moreover, the underlying mechanism is relevant if one could incorporate into priorities differences in risk responsiveness across population groups (e.g. see Figure 4h). Estimates for different nations and across states in the United States suggest the risk responsiveness ($\alpha$) varies much, by orders of magnitude, across communities (Lim and Rahmandad, 2022). Whether due to cultural, political, social, or economic reasons, some communities tolerate much higher death rates than others before they start implementing NPIs. These communities have thus ended up suffering much higher death rates during the pandemic, creating major disparities in the toll of COVID-19 across race, socioeconomic, and geographic groups (Mackey et al., 2021). Identifying and prioritizing these communities for vaccination may offer the highest benefit in terms of saving lives (Wrigley-Field et al., 2021) and livelihoods.

Our results should be interpreted with an eye on some key uncertainties and limitations. We explored some of those uncertainties in our robustness section, noting for example that the Elderly-First priority becomes more attractive when vaccines are protective against deaths but not against transmission. Moreover, a broader set of boundary conditions remain. First, the current model assumes behavioral responses are largely driven by risk of death. Results may change if the number of cases (or related proxies) were the primary driver of the behavioral responses because cases may rise among the vaccinated without a corresponding increase in deaths. Second, the model does not account for loss of immunity, from vaccines or infection. Current estimates suggest the immunity loss to be significant and happening within a few months or faster (Arbel et al., 2021). Rapid loss of immunity would call for continuous vaccination of all groups (i.e. boosters) and somewhat mutes the prioritization question after the first wave of vaccination,
although the problem could become important again if new vaccines are introduced to tackle new variants of the virus, or if the supply of vaccine is chronically below demand. Third, the time constants for risk perception and response matter: in the extreme, long delays in risk perception effectively eliminate the behavioral feedback. Given the asymmetry in relaxation of risks, communities with slow risk relaxation may find the feedback to be less critical during a short vaccination period because their perceived risk remains high for longer. In the case of the United States, the estimated (downward) adjustment time (of 46 days) is short enough to shift the optimal priority towards High-Contact-First for vaccination periods over 4–6 months; that period may extend longer for nations that do not quickly adjust their risk perception to the reduced death rates. There are other simplifying assumptions worth noting: the model ignores changes in fatality due to prior infections, does not account for changes in vaccine acceptance that may depend on prioritization policy, abstracts away from multidose vaccines, excludes variants, and does not consider economic trade-offs. Finally, we only considered two simple prioritization heuristics when more complex dynamic prioritization schemes could be designed to leverage the mechanisms identified in the current study. Considering these and other limitations of the current study, one should not treat the results as unequivocal policy recommendations, but as an important reminder that behavioral feedbacks should be accounted for in designing vaccination policies, otherwise both intuitions and modeling results could be misleading with thousands of lives at stake.

Even if promising in theory, practical roadblocks to adopting prioritization based on contact rate or responsiveness may be significant. The intuition that vaccinating those most at risk (elderly) saves the most lives is so strong that many policymakers will have a hard time trusting a model-based recommendation that goes against their first intuition. Even if policymakers were convinced by the logic of the model, convincing the public of the merits of the policy may not be easy, and thus a contact (or responsiveness)-based prioritization policy may create a backlash. The alternative may also be more complex in terms of logistics: those with the highest demand for vaccines are often people most responsive to the risk, exactly the groups our analysis suggests should be deprioritized at the beginning. On the other hand, it may be harder to find and vaccinate the people least responsive to risk first (those contributing most to the ongoing transmissions and thus prioritized). Overcoming these challenges may not be easy but could be feasible. Prioritization of higher-contact individuals, as well as those least able to change their behaviors in response to COVID-19 risks based on occupation (e.g. healthcare workers, first-responders, the incarcerated, high-contact service workers) offers one pathway to implement this policy. Another is to focus on geographic allocation of vaccines based on prior death rates (Wrigley-Field et al., 2021): those communities that have suffered the greatest COVID-19 deaths to-date could get the...
first doses of vaccines, offering an intuitive and practical alternative prioritization. These and more creative alternatives may be feasible to design, justify, and implement and could have saved many thousands of lives while enabling a faster return to normal life for everybody. The broader insights may still be useful in light of undervaccination in many countries, the emerging variants, and the need for new vaccines; they also contribute to a more informed discussion of vaccination prioritization beyond COVID-19.

Acknowledgements

Navid Ghaffarzadegan, Tse Yang Lim, John Sterman, and Kim Thompson provided helpful comments. The author is very thankful to Tom Fiddeman and Ventana Systems for providing the Vensim parallel simulation environment for this research.

Data availability statement

All models, data, and analysis code are available as an online supplement hosted by the journal and publicly available at https://osf.io/36zem/?view_only=d933dac244e64f4ebad15cfacc41b270

Biography

Hazhir Rahmandad is an Associate Professor of System Dynamics at the MIT Sloan School of Management. Hazhir’s research applies dynamic modeling to complex organizational and public health problems from strategy to understanding pandemics. His methodological work contributes to parameter estimation methods for dynamic models and aggregation of prior statistical findings.

References

Alimohamadi Y, Taghdir M, Sepandi M. 2020. Estimate of the basic reproduction number for COVID-19: a systematic review and meta-analysis. *Journal of Preventive Medicine and Public Health* 53(3): 151.

Arbel R, Hammerman A, Sergienko R, Friger M, Peretz A, Netzer D, Yaron S. 2021. BNT162b2 vaccine booster and mortality due to Covid-19. *New England Journal of Medicine* 385(26): 2413–2420.

Bagnoli F, Liò P, Sguanci L. 2007. Risk perception in epidemic modeling. *Physical Review E* 76(6): 061904.
Bernal JL, Andrews N, Gower C, Robertson C, Stowe J, Tessier E, Simmons R, Cottrell S, Roberts R, O'Doherty M. 2021. Effectiveness of the Pfizer-BioNTech and Oxford-AstraZeneca vaccines on covid-19 related symptoms, hospital admissions, and mortality in older adults in England: Test negative case-control study. BMJ Clinical Research 373: n1088.

Bubar KM, Reinholt K, Kissler SM, Lipsitch M, Cobey S, Grad YH, Larremore DB. 2021. Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. Science 371(6532): 916–921.

Buckner JH, Chowell G, Springborn MR. 2021. Dynamic prioritization of COVID-19 vaccines when social distancing is limited for essential workers. Proceedings of the National Academy of Sciences 118(16): e2025786118.

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. Nature Medicine 26(8): 1205–1211.

Eksin C, Paarporn K, Weitz JS. 2019. Systematic biases in disease forecasting—the role of behavior change. Epidemics 27: 96–105.

Fitzpatrick MC, Galvani AP. 2021. Optimizing age-specific vaccination. Science 371(6532): 890–891.

Funk S, Salathe M, Jansen VAA. 2010. Modelling the influence of human behaviour on the spread of infectious diseases: a review. Journal of the Royal Society Interface 7(50): 1247–1256.

Gallagher ME, Sieben AJ, Nelson KN, Kraay AN, Orenstein WA, Lopman B, Handel A, Koelle K. 2021. Indirect benefits are a crucial consideration when evaluating SARS-CoV-2 vaccine candidates. Nature Medicine 27(1): 4–5.

Goldstein JR, Cassidy T, Wachter KW. 2021. Vaccinating the oldest against COVID-19 saves both the most lives and most years of life. Proceedings of the National Academy of Sciences of the United States of America 118(11): e2026322118.

Hao X, Cheng S, Wu D, Wu T, Lin X, Wang C. 2020. Reconstruction of the full transmission dynamics of COVID-19 in Wuhan. Nature 584(7821): 420–424.

Jentsch PC, Anand M, Bauch CT. 2021. Prioritising COVID-19 vaccination in changing social and epidemiological landscapes: a mathematical modelling study. The Lancet Infectious Diseases 21(8): 1097–1106.

Levin AT, Hanage WP, Owusu-Boaitey N, Cochran KB, Walsh SP, Meyerowitz-Katz G. 2020. Assessing the age specificity of infection fatality rates for COVID-19: systematic review, meta-analysis, and public policy implications. European Journal of Epidemiology 35(12): 1123–1138.

Liang LL, Kuo HS, Ho HJ, Wu CY. 2021. COVID-19 vaccinations are associated with reduced fatality rates: evidence from cross-county quasi-experiments. Journal of Global Health 11: 05019.

Lim TY, Rahmandad H. 2022. Responsiveness to risk explains large variation in COVID-19 mortality across countries. Available at SSRN 3747254.

Lipsitch M, Dean NE. 2020. Understanding COVID-19 vaccine efficacy. Science 370(6518): 763–765.

Mackey K, Ayers CK, Kondo KK, Saha S, Advani SM, Young S, Spencer H, Rusek M, Anderson J, Veazie S, Smith M, Kansagara D. 2021. Racial and ethnic disparities in COVID-19-related infections, hospitalizations, and deaths: a systematic review. Annals of Internal Medicine 174(3): 362–373.
Masters NB, Shih SF, Bukoff A, Akel KB, Kobayashi LC, Miller AL, Harapan H, Lu Y, Wagner AL. 2020. Social distancing in response to the novel coronavirus (COVID-19) in the United States. *PLoS One* **15**(9): e0239025.

Mathieu E, Ritchie H, Ortiz-Ospina E, Roser M, Hasell J, Appel C, Giattino C, Rodes-Guirao L. 2021. A global database of COVID-19 vaccinations. *Nature Human Behaviour* **5**(7): 947–953.

Moore S, Hill EM, Dyson L, Tildesley MJ, Keeling MJ. 2021. Modelling optimal vaccination strategy for SARS-CoV-2 in the UK. *PLoS Computational Biology* **17**(5): e1008849.

Perrings C, Castillo-Chavez C, Chowell G, Daszak P, Fenichel EP, Finnoo D, Horan RD, Kilpatrick AM, Kinzig AP, Kuminoff NV, Levin S, Morin B, Smith KF, Springborn M. 2014. Merging economics and epidemiology to improve the prediction and Management of Infectious Disease. *EcoHealth* **11**(4): 464–475.

Prem K, Zandvoort KV, Klepac P, Eggo RM, Davies NG, Centre for the Mathematical Modelling of Infectious Diseases COVID-19 Working Group, Cook AR, Jit M. 2021. Projecting contact matrices in 177 geographical regions: an update and comparison with empirical data for the COVID-19 era. *PLoS Computational Biology* **17**(7): e1009098.

Rahmandad H, Lim TY, Sterman J. 2021. Behavioral dynamics of COVID-19: estimating under-reporting, multiple waves, and adherence fatigue across 92 nations. *System Dynamics Review* **37**(1): 5–31.

Rahmandad H, Xu R, Ghaffarzadeh N. 2022. Enhancing long-term forecasting: learning from COVID-19 models. *PLoS Computational Biology* **18**(5): e1010100.

Rumain B, Schneiderman M, Geliebter A. 2021. Prevalence of COVID-19 in adolescents and youth compared with older adults in states experiencing surges. *PLoS One* **16**(3): e0242587.

Struben J. 2020. The coronavirus disease (COVID-19) pandemic: simulation-based assessment of outbreak responses and postpeak strategies. *System Dynamics Review* **36**(3): 247–293.

WHO. 2020. The global health observatory. Retrieved 17 June 2020, from https://www.who.int/data/gho/data/indicators

Wrigley-Field E, Kiang MV, Riley AR, Barbieri M, Chen YH, Duchowny KA, Matthay EC, Van Riper D, Jategaslan K, Bibbins-Domingo K, Leider JP. 2021. Geographically targeted COVID-19 vaccination is more equitable and averts more deaths than age-based thresholds alone. *Science Advances* **7**(40): eabj2099.

Xu R, Rahmandad H, Gupta M, DiGennaro C, Ghaffarzadeh N, Amini H, Jalali MS. 2021. Weather, air pollution, and SARS-CoV-2 transmission: a global analysis. *The Lancet Planetary Health* **5**(10): e671–e680.

**Supporting information**

Additional supporting information may be found in the online version of this article at the publisher’s website.

**Appendix S1: Supporting Information**