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Modelling interventions to control COVID-19 outbreaks in a refugee camp

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ABSTRACT

Background In the absence of effective treatments or vaccines, non-pharmaceutical interventions are the mainstay of control in the COVID-19 pandemic. Refugee populations in displacement camps live under adverse conditions that are likely to favour the spread of disease. To date, only a few cases of COVID-19 have appeared in refugee camps, and whether feasible non-pharmaceutical interventions can prevent the spread of the SARS-CoV-2 virus in such settings remains untested.

Methods We constructed the first spatially explicit agent-based model of a COVID-19 outbreak in a refugee camp, and applied it to evaluate feasible non-pharmaceutical interventions. We parameterised the model using published data on the transmission rates and progression dynamics of COVID-19, and demographic and spatial data from Europe's largest refugee camp, the Moria displacement camp on Lesbos, Greece. We simulated COVID-19 epidemics with and without four feasible interventions.

Results Spatial subdivision of the camp ('sectoring') was able to 'flatten the curve', reducing peak infection by up to 70% and delaying peak infection by up to several months. The use of face masks coupled with the efficient isolation of infected individuals reduced the overall incidence of infection, and sometimes averted epidemics altogether. These interventions must be implemented quickly in order to be maximally effective. Lockdowns had only small effects on COVID-19 dynamics.

Conclusions Agent-based models are powerful tools for forecasting the spread of disease in spatially structured and heterogeneous populations. Our findings suggest that feasible interventions can slow the spread of COVID-19 in a refugee camp setting, and provide an evidence base for camp managers planning intervention strategies. Our model can be modified to study other closed populations at risk from COVID-19 or future epidemics.

Key questions

What is already known?

- ► Conditions in refugee camps, including overcrowding, poor sanitation, and frequent close contact among residents in food lines and at shared toilets, are expected to promote the spread of COVID-19.
- ► Non-pharmaceutical interventions such as the use of face masks, lockdowns, and mandatory social distancing have slowed the spread of COVID-19 in some non-camp populations.
- ► No empirical data exist to show whether similar interventions can be successful in refugee camps.

What are the new findings?

- ► Agent-based simulations show that face mask use, spatial subdivision, and the efficient isolation of suspected cases may slow the spread of COVID-19 in refugee camps.
- ► Lockdowns alone are unlikely to affect COVID-19 dynamics.
- ► Interventions must be implemented quickly to be maximally effective.

What do the new findings imply?

- ► Well-planned sets of non-pharmaceutical interventions have the potential to save lives during COVID-19 outbreaks in refugee camps.
- ► Results may be transferable to other epidemics and other vulnerable populations.

Authors' Note: The model reported in this paper simulates a COVID-19 outbreak in the Moria refugee camp. At the time of writing, Moria was the largest refugee camp in Europe, and COVID-19 had not yet appeared in the camp. By the time of publication, two important events had occurred. On 3 September 2020, a first case of COVID-19 was detected in Moria, and there is evidence of onward transmission. Then, on 8 September, a fire broke out and the camp was destroyed. Fortunately, there were no fatalities. A new camp is now being built. The results we present here will be valuable to managers planning the new camp, and may be applicable to similar displacement camps elsewhere. We present the paper as originally written, and we place the results in the context of the new situation on the ground in the discussion.

INTRODUCTION

There are >70 million refugees and internally displaced persons worldwide, including >20 million living in displacement camps.[1] Displaced populations are expected to be vulnerable to COVID-19 due to poor nutrition, high rates of pre-existing disease, and inadequate access to healthcare.[2–5] COVID-19 may spread rapidly in displacement camps due to overcrowding, poor sanitation, and frequent close contact among residents (eg, in food lines, at shared toilets, and at shared washing facilities).[5–7] Truelove *et al*[8] used a computational simulation to study a potential COVID-19 outbreak in a population modelled on the Kutupalong-Balukhali refugee camp in Bangladesh, and estimated that up to 98% of the population could become infected over a short period, overwhelming the camp's limited medical facilities. Many countries have imposed interventions such as mandatory social distancing, isolation of confirmed cases, or general lockdowns to slow the spread of COVID-19, and in some cases these have been successful.[9–11] However, whether similar interventions can be effective in the uniquely challenging setting of a displacement camp is unknown.[7]

The Moria refugee camp on the island of Lesbos, Greece, was Europe's largest displacement camp. A former military barracks, it was converted into a refugee reception facility with the arrival of people fleeing the Syrian civil war in 2015. It was designed to hold 3000 people, but by February of 2020 it housed nearly 20 000 people in an area of <1 km^2.[12] Non-governmental organisations working in Moria reported severe overcrowding, poor sanitation, a lack of hygiene facilities (eg, toilets, showers, 24-hour running water), and queuing at central facilities (eg, food lines).[13 14] The population had little access to healthcare outside the camp, and there was a lack of adequate healthcare in the camp (eg, no 24-hour service, provided only by volunteer organisations). Approximately 5% of the camp's population was highly vulnerable to COVID-19 infection, including people with chronic health conditions and those over 65 years of age. COVID-19 had not yet reached the camp. However, cases of COVID-19 had appeared on Lesbos,[13 15] placing the camp at risk.

Although refugee camp populations are believed to be vulnerable to COVID-19 epidemics, there is little data on the spread of COVID-19 in refugee camps, and no data to show which interventions are best able to combat the spread of the disease in this setting. In the absence of empirical data, mathematical and computational models can provide an evidence base for managers planning intervention strategies.

Displacement camp populations are spatially structured. In Moria, residents interacted most frequently with other members of their own households. They interacted with members of nearby households during daily activities or at shared toilet facilities, and they interacted with residents from all parts of the camp at the camp's single shared food line. Such an interaction structure can affect how COVID-19 spreads through a camp, and interventions that change the interaction structure may alter the trajectory of outbreaks. Previous modelling of COVID-19 outbreaks in displacement camps used compartmental models,[8] which assume that populations are well-mixed. Agent-based models that track individuals through simulated daily movements are better able to capture transmission dynamics in structured populations.[16]

We developed a spatially explicit agent-based model to simulate how COVID-19 might spread in the Moria camp without or with a set of possible interventions. We estimated the parameters that control SARS-CoV-2 transmission and COVID-19 progression from the literature, and we modelled the camp structure, population, and the movement of individuals within the camp to match estimates provided by camp medical workers. We simulated four non-pharmaceutical interventions that may be feasible in displacement camps: (i) sectoring: dividing the camp into subunits with separate food lines and services, and asking residents to use only the services in their own sectors; (ii) face masks: issuing face masks to residents and educating residents about face mask use; (iii) remove-and-isolate: identifying and isolating infectious individuals and their families; and (iv) lockdown: requiring residents to remain in or near their homes.

We analysed these interventions alone and in combination, and studied how the timing of interventions affects the duration and intensity of epidemics. Our study represents the first attempt to predict optimal intervention strategies for a refugee camp population. The results will be useful to managers planning responses to COVID-19 for densely populated displacement or detention camps, and our model can be modified to study other epidemics in similar closed populations.

METHODS

We simulated COVID-19 outbreaks in a model population based on the Moria refugee camp (online supplemental information S1). The model population includes 18 700 individuals each characterised by age, sex, ethnic group, whether they have a pre-existing condition that makes them particularly vulnerable to COVID-19, and by their disease state. Each individual is a member of a household that occupies either an isobox (mean occupancy 10) or a tent (mean occupancy 4). Isoboxes and tents are positioned on a 1 km^2 square (ie, the 'camp', online supplemental figure S1.1), with isoboxes nearer the centre and tents nearer the periphery, as in Moria. Households from the same ethnic group are spatially clustered. The camp includes 144 toilets distributed evenly around the camp, and one central food line that forms three times per day. Each individual has a home range centred on its tent or isobox, and interacts with others with overlapping home ranges. Individuals interact more frequently with others from the same ethnic group. Individuals visit the toilet nearest their home three times per day, and a subset of individuals visits the food line each time it forms. COVID-19 can be transmitted from infectious to susceptible individuals within households, or during interactions in the home range, in toilet lines, or in food lines, and the probability of transmission depends on the duration and intensity of the interaction.[17 18]

Individuals begin each simulation in the susceptible state. If an individual is infected with COVID-19, it passes through exposed, pre-symptomatic, and diseased states before recovery (online supplemental figure S1.2). The diseased state can be symptomatic or asymptomatic. The length of time individuals spend in each state and the probability that the diseased state is symptomatic are age-dependent and estimated from the literature.[19–26] Individuals in the pre-symptomatic and diseased states are infectious. All individuals can interact at toilets, but individuals with symptoms do not attend food lines or interact in their home ranges. We assumed that recovered individuals cannot be re-infected.

The transmission probabilities per interaction for COVID-19 are poorly understood. Therefore, we modelled low-transmission and high-transmission scenarios based on low-end[17 18] and high-end[23 27] estimates from the literature (online supplemental information S2). R_0 in the low-transmission scenario is slightly higher than in Chinese cities before intervention,[28] and R_0 in high-transmission scenario is similar to that on the Diamond Princess cruise ship before interventions were imposed.[29] The true transmission probabilities for COVID-19 in Moria would have been likely to fall between these estimates. How individuals used space and interacted with others in Moria or other refugee camps is also poorly understood. Therefore, we modelled low-movement and high-movement scenarios and low-interaction and high-interaction scenarios. In the body of this paper, we present results for the low-movement, high-interaction scenario, but results are qualitatively similar for other scenario combinations (online supplemental tables S1–S11).

We modelled COVID-19 outbreaks without interventions and in the presence of four interventions feasible for displacement camps: (i) sectoring, (ii) face mask use, (iii) remove-and-isolate, and (iv) lockdown. In sectoring, the central food line is eliminated and the camp is divided into n sectors. Each sector has its own food line, and the members of each household use only the food line in their own sector. The time individuals spend in food lines scales with $1/\sqrt{n}$. Thus, with sectoring, transmission in food lines is reduced and becomes local rather than global. Many policies or behaviours might reduce the probability that infection is transmitted when individuals interact (eg, the use of face masks, frequent hand washing, maintaining safe distances from others). Outside of refugee camps, public health managers have bundled these policies into coherent transmission reduction plans. In Moria, frequent hand washing and maintaining safe distances was impossible.[5] However, Moria residents were provided with face masks, and healthcare workers in the camp reported that these were widely used. Therefore, we focused on face mask use. To simulate face mask use, we reduced the odds of transmission by a factor of 0.32 for all individuals in interactions outside their households. A similar reduction has been achieved for other respiratory viruses by the widespread use of surgical masks.[30] In Moria, entire households ate and slept in tents or isoboxes without subdivisions, and we assumed that face masks would not be effective at reducing transmission in such a setting. In remove-and-isolate, individuals with symptoms are detected with some probability b on each day. If a symptomatic individual is detected, their entire household is removed from the camp to an isolation facility, and no further transmission from that household to other households can occur. By removing entire households, camp managers hope to remove asymptomatic and presymptomatic cases from the population, and to avoid separating carers from their families. The detection probability b controls the efficiency of the remove-and-isolate intervention. At the time of writing, there was no programme in Moria to test asymptomatic people for COVID-19, and therefore we assumed that asymptomatic infections would not be detected. In practice, detection is likely to require self-reporting of symptoms by camp residents, and therefore this intervention will rely on active cooperation between camp residents and managers. Finally, in lockdown, individuals are constrained to remain within some radius r_l of their homes. We assumed that a proportion v_l of individuals violates the lockdown. By controlling r_l and v_l, we modelled lockdowns with less or greater compliance. In this paper, we report results for interventions where n=16, b=2, r_l=10 m and v_l=0.10. We report results for other parameter values in online supplemental tables S3–S8.

To simulate COVID-19 outbreaks, we moved one randomly selected individual in the population to the exposed state. We iterated the model through discrete timesteps that correspond to days until there were no infected individuals remaining in the population. If fewer than 20 individuals became infected during an outbreak, we recorded that an epidemic had been averted. If the epidemic was not averted, then we recorded the peak infection (ie, the highest proportion of the population that was infected on any day), the day on which the peak infection occurred, and the total proportion of the population that became infected during the epidemic. For remove-and-isolate interventions, we also recorded the maximum number of individuals in isolation on any day. We conducted 200 simulations for each combination of scenario and intervention that we studied (89 600 total simulations).

RESULTS

In the absence of interventions, the introduction of a single COVID-19 case into the model population almost always (≥97%) led to epidemics in both the low-transmission and high-transmission scenarios (table 1 and online supplemental table S1). In the low-transmission scenario, the median peak infection included 67% of the population and occurred 55 days after the index case appeared (figure 1A). In the high-transmission scenario, the median peak infection included 98% of the population and occurred on day 25 (figure 1B). In total, 98% and >99% of the population became infected

Table 1 Total proportion of the population infected and epidemics averted without or with interventions in the low-transmission and high-transmission scenarios

	Without face masks		With face masks	
Intervention	Total proportion infected	Epidemics averted	Total proportion infected	Epidemics averted
Low transmission				
No intervention	0.98 (0.98–0.98)	0.03	0.87 (0.87–0.88)	0.17
Sectoring	0.96 (0.96–0.96)	0.05	0.77 (0.76–0.78)	0.26
Remove-and-isolate	0.87 (0.86–0.87)	0.27	0.006 (0.003–0.013)	0.66
Lockdown	0.98 (0.98–0.99)	0.04	0.87 (0.87–0.88)	0.14
High transmission				
No intervention	>0.99	<0.01	>0.99	<0.01
Sectoring	>0.99	<0.01	>0.99	0.01
Remove-and-isolate	>0.99	0.02	>0.99	0.06
Lockdown	>0.99	<0.01	>0.99	<0.01

For total proportions infected, we report medians and IQRs for all simulations in which epidemics occurred. For epidemics averted, we report proportions of 200 simulations. Grey cells indicate simulations without interventions.

in the low-transmission and high-transmission scenarios, respectively (table 1).

Interventions were able to slow or stop the spread of COVID-19 (figure 1; table 1 and online supplemental tables S2–S11). Sectoring reduced and delayed the peak infection in both the low-transmission (median peak infection 20% on day 98) and high-transmission (median peak infection 41% on day 51) scenarios, but most individuals ultimately became infected (low-transmission scenario: total infection 96%, epidemics averted 5%; high-transmission scenario: total infection >99%, epidemics averted <1%). Face mask use reduced and delayed the peak infection in the low-transmission scenario (median peak infection 31% on day 96) but was less effective in the high-transmission scenario (median peak infection 90% on day 36) (figure 1C,D). In the low-transmission scenario, face mask use also reduced the proportion of the population that became infected (total infection 87%, epidemics averted 17%). In the low-transmission scenario, remove-and-isolate interventions averted 27% of epidemics. When epidemics occurred, remove-and-isolate interventions reduced and delayed the peak infection, but required concurrently isolating more than half of the population (online supplemental table S4). In the high-transmission scenario, remove-and-isolate interventions had little effect on epidemics (median peak infection 97% on day 27). Lockdowns had little effect on epidemics in either the low-transmission (median peak infection 66% on day 57) or high-transmission (median peak infection >98% on day 26) scenarios.

The use of face masks augmented the effects of sectoring and remove-and-isolate interventions (figure 1C,D; table 1, online supplemental tables S6–S8). In the low-transmission scenario, sectoring combined with face mask use reduced the median peak infection to 9% on day 167, limited total infection to 77% of the population and averted 26% of epidemics. In the high-transmission scenario, sectoring combined with face mask use reduced the median peak infection to 28% of the population on day 76, but >99% of the population eventually became infected. In the low-transmission scenario, remove-and-isolate combined with face mask use prevented most epidemics (median peak infection 0.2%, total infection 0.6%, 66% of epidemics averted). However, in the high-transmission scenario, remove-and-isolate combined with face mask use was little better than face masks alone. Similarly, in both scenarios, lockdown combined with face mask use was little better than face masks alone.

Sectoring and remove-and-isolate interventions helped control epidemics, but had to be implemented early to be maximally effective (figure 2; online supplemental tables S9 and S10). If face masks were used but sectoring was not implemented until 1% of the population showed symptoms in the low-transmission scenario, then the median peak infection increased from 9% to 19% and the proportion of epidemics averted dropped from 26% to 14%. In the high-transmission scenario, peak infection increased from 28% on day 76 to 78% on day 38. If remove-and-isolate was not implemented until 1% of the population showed symptoms in the low-transmission scenario, then the median peak infection increased from 0.2% to 8.6%, the median total infection increased from 0.6% to 30% and epidemics averted dropped from 66% to 10%. In the high-transmission scenario, remove-and-isolate was not effective even if it was implemented early (figure 1D).

DISCUSSION

Displacement camp populations are expected to be vulnerable to COVID-19 and other epidemics due to poor sanitation, crowded conditions, high rates of pre-existing disease, and inadequate access to healthcare.[2 3 6] Without intervention, a single case of COVID-19 introduced into

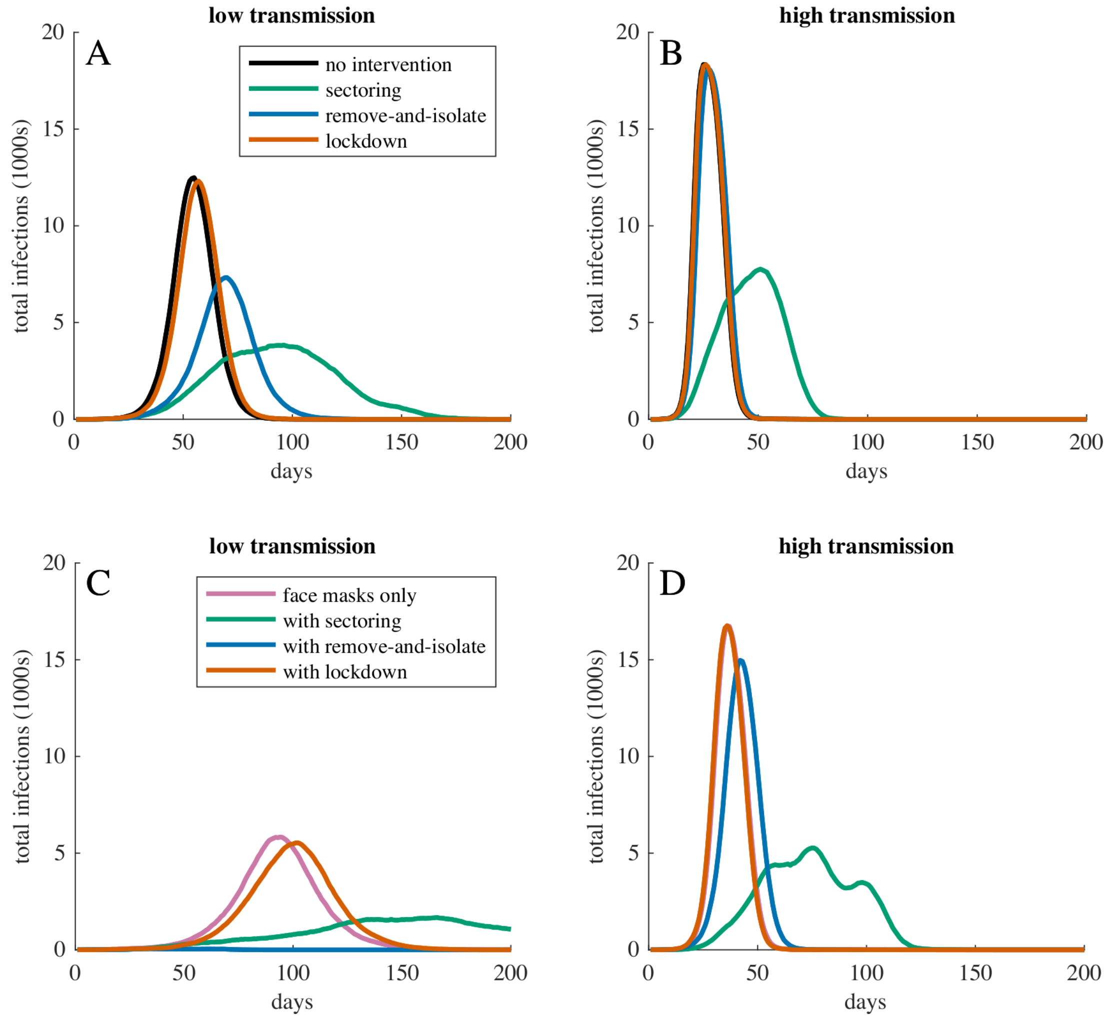

Figure 1 Total infections over time for COVID-19 outbreaks with different interventions in populations with low movement, high interaction, and (A, C) low or (B, D) high transmission probabilities. Panels (A, B) show dynamics without face mask use, and (C, D) show dynamics with face mask use. Curves show the most representative simulation (ie, the simulation with the peak infection and peak infection date closest to the median) for the corresponding intervention. When transmission probabilities were high (B, D), only sectoring meaningfully reduced or delayed peak infection. When transmission probabilities were sufficiently low (ie, low transmission with face mask use, C), remove-and-isolate interventions were able to prevent epidemics. In panel (D), the line for face mask use only is concealed behind the line for face mask use with lockdown.

our model almost always led to a severe epidemic that rapidly spread through the entire population. Sectoring, remove-and-isolate interventions, and the use of face masks slowed the spread of infection, and in some cases stopped epidemics altogether. These interventions must be implemented early to be maximally effective. Our results can help displacement camp managers choose the most effective interventions to protect vulnerable populations from COVID-19 and other epidemics.

Dividing camps into sectors with separate food lines reduced and delayed the infection peak. Reducing the number of people that are infected at the same time may alleviate pressure on limited medical services both in camps and in surrounding communities.[10] Our model assumes that sectoring can prevent meetings, and thus transmission, between individuals from distant parts of the camp. If this is not true, then sectoring may be less effective than our model suggests. Furthermore, managing multiple food lines may require more staff and resources than running a single line, and so may be difficult to achieve for some camps. Finally, while sectoring slowed the rate at which epidemics spread through the camp, it rarely averted epidemics altogether and had only a small effect on the total number of individuals that became infected. Thus, while sectoring may reduce pressure on medical services, sectoring alone is unlikely to protect vulnerable members of the population who may be at heightened risk due to COVID-19 with or without medical attention. However, by slowing the spread of infection, sectoring may give managers more time to move vulnerable people to safety.

In contrast to sectoring, both face mask use and remove-and-isolate interventions reduced the total number of people that became infected. When infectiousness was at the low end of published estimates, face masks coupled with an efficient remove-and-isolate

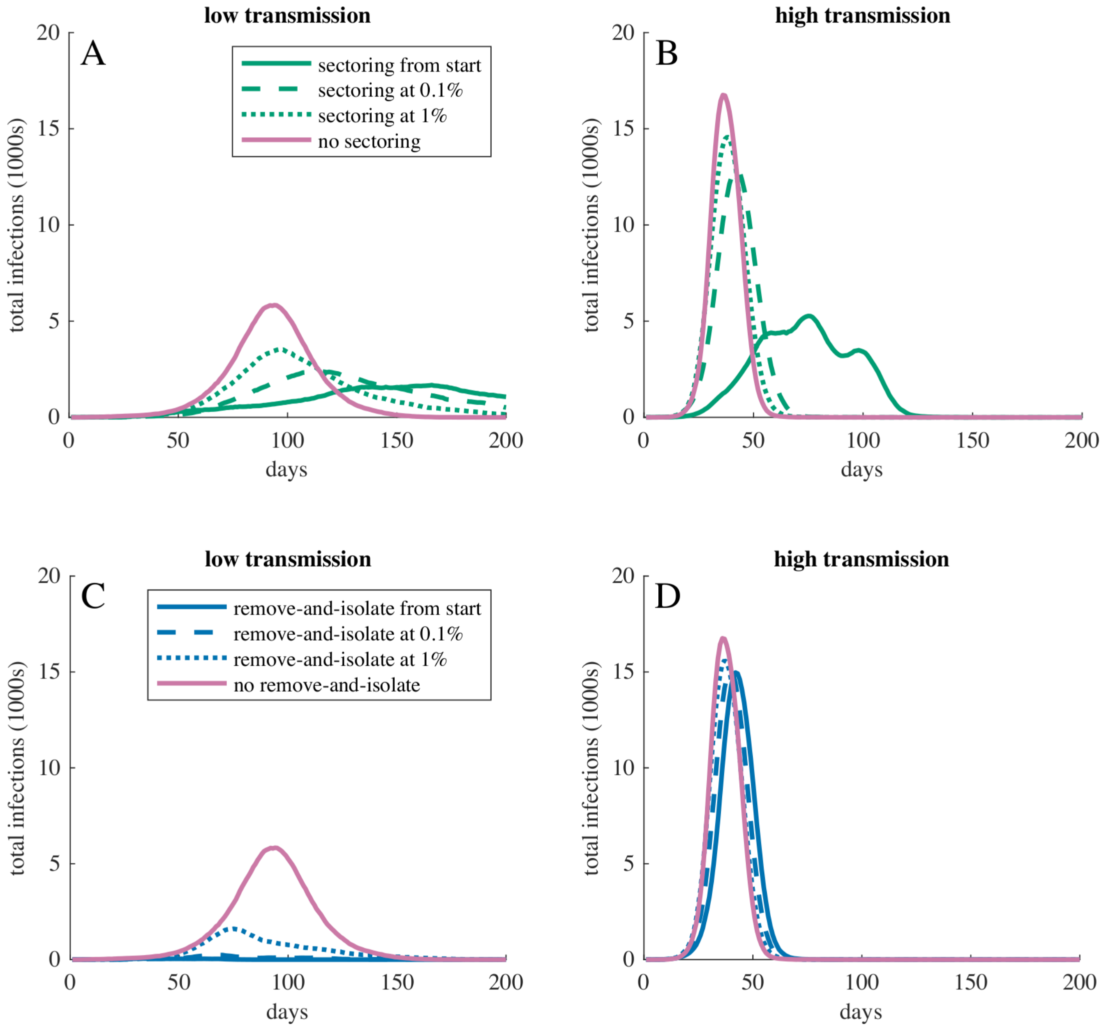

Figure 2 Total infections over time for COVID-19 outbreaks when (A, B) sectoring or (C, D) remove-and-isolate interventions started before the virus arrived, when 0.1% of the population had symptoms, when 1% of the population had symptoms, or not at all. Face masks were in use throughout all simulations. (A, C) show the low-transmission and (B, D) show the high-transmission scenario. Curves show the most representative simulation for the corresponding intervention. In all cases, a delayed start to the intervention resulted in higher peak infection. In the high-transmission scenario, even a slightly delayed start eliminated most gains that could be achieved by the intervention.

intervention prevented >65% of COVID-19 introductions from becoming epidemics and limited the median total infection to <1% of the population. Combining these interventions with sectoring produced further gains. However, the effectiveness of face masks and remove-and-isolate interventions was sensitive to the infectiousness of the virus. If the infectiousness was at the high end of published estimates, then face mask use and remove-and-isolate interventions had little effect on epidemics. Moreover, interventions in practice may not be as effective as those we modelled. Our estimates for the effectiveness of face masks are based on short-term studies.[30] If people's commitment to using face masks erodes over time, then face masks may become less effective. To our knowledge, this has not been studied. Remove-and-isolate interventions require that managers are able to quickly and accurately detect COVID-19 cases, and may be resource-intensive if they fail to avert epidemics completely. Because people must be maintained in isolation until managers are sure they are no longer infectious, the maximum number of people in isolation will usually be larger than the peak infection (online supplemental tables S4, S7, S10 and S11). If managers' capacity to remove and isolate infected individuals is overwhelmed, then remove-and-isolate interventions will fail.

In our model, requiring individuals to remain within a small radius of their homes had little effect on epidemics. Even during lockdowns, transmission continued at shared toilets and food lines. Moreover, the lockdowns we studied were ambitious. For results reported in this paper, we assumed that 10% of individuals would violate the lockdown rule, but in the UK >25% of young women and >50% of young men admit to regularly violating lockdown rules[31] and similar patterns have been reported in the USA.[32] Thus, it is not clear that lockdowns of the sort we modelled will be effective at combatting the spread of COVID-19 in refugee camps. However, the number of interactions that individuals engage in each day can affect the dynamics of epidemics (compare shaded with unshaded rows in online supplemental tables S1–S11). Thus, encouraging camp residents to limit their daily interactions may be a viable tool for slowing epidemics.

Sectoring and remove-and-isolate interventions must be implemented from the beginning of an outbreak if they are to be maximally successful. If interventions are not in place when the virus arrives, the virus can rapidly spread to all parts of the camp. It then becomes very difficult to contain. Background rates of respiratory infection in displacement camps are high,[3 4] which may make new infections difficult to detect. Thus, population managers should be prepared to impose interventions at the first threat of epidemic.

The parameter values assigned in this study were estimated with uncertainty. The transmission probabilities for COVID-19 were estimated from the literature, which is rapidly evolving. The parameter values that describe how individuals move and interact in the camp were estimated from consultation with camp medical staff, and empirical data to confirm these estimates do not exist for Moria or any other displacement camp. Different transmission probabilities, and to a lesser extent different interaction rates, within the plausible range of values result in very different epidemics. Until parameter values can be more accurately estimated, our model should not be used to make quantitative predictions about peak infection rates, times to peak infection, or proportions of epidemics averted. Some qualitative predictions of the model also depend on the parameter values. For example, in the low-transmission scenario, combinations of the interventions we modelled can stop the spread of COVID-19. In the high-transmission scenario, sectoring can slow the epidemic, but almost the entire population is eventually infected. Thus, in the high-transmission scenario, the removal and shielding of vulnerable individuals (ie, those over 65 years of age or with pre-existing conditions[2 25 26]) may be the only intervention that saves lives. Per interaction transmission rates are notoriously difficult to estimate empirically, and interaction rates and networks among members of vulnerable populations have rarely been studied. These are key parameters in agent-based epidemiological models, and with accurate parameter values agent-based models are better than classical compartmental models at simulating the spread of disease in structured, heterogeneous populations.[16] Thus, empirical work to estimate interaction rates and per interaction transmission probabilities may be of great value. We assumed that individuals with symptoms do not attend food lines or interact with others in their home ranges, and if this assumption is violated then epidemics may spread more rapidly than our model predicts. Finally, our model assumes that individuals that have recovered from COVID-19 cannot be re-infected at least for the duration of the epidemic, and evidence to support this assumption is limited.[33] As more empirical data on COVID-19 become available, our model can be updated to provide more accurate predictions.

Our model and others[8] predict that COVID-19 could spread rapidly in refugee camps, but at the time of writing there had been no extensive outbreak in a refugee camp setting. In Moria, this may be because the camp was well protected. Prior to August 2020, there were only a few cases of COVID-19 on Lesbos, and these were effectively isolated. There was little interaction between camp residents and the local population, and new arrivals to the camp were screened and quarantined before admission.[34] When the virus arrived in the camp, there is at least some evidence that it did spread rapidly, consistent with model predictions. The first symptomatic COVID-19 case was detected in Moria on 3 September. By 8 September, 35 additional cases had been detected,[35] and by 22 September >240 people from the Moria population had tested positive for the virus,[36 37] although it is not known if the case detected on 3 September was the source of this outbreak. In other refugee camps, initial cases of COVID-19 have not been followed by major outbreaks, although COVID-19 in refugee camps may be systematically under-reported.[38]

One reason that individual COVID-19 cases might seed fewer epidemics in practice than in our model is an overdispersion of transmission events. There is growing evidence that some infected individuals produce many secondary transmissions, while others produce none at all.[39] This may be because some individuals have more social interactions than others, or it may be because some individuals have a higher probability of transmitting the virus in each interaction. If some individuals have low-transmission probabilities, then a randomly chosen COVID-19 case may be less likely to seed an epidemic than if all individuals have the same transmission probabilities. However, if overdispersion is driven primarily by differences in interaction rates, then epidemics may be more difficult to control, because individuals that are more likely to become infected will also be more likely to infect others. In our model, transmission events are moderately overdispersed, because some individuals have larger households or more densely occupied home ranges or remain asymptomatic longer than others (online supplemental table S12). However, overdispersion of transmission events in real populations appears to be greater than in our model.[39] As more data on the mechanisms of overdispersion become available, new modelling work can study how overdispersion affects epidemic control.

The model we present here is the first attempt to evaluate potential interventions to control the spread of COVID-19 in a displacement camp. Despite remaining uncertainties, our results can provide valuable guidance to camp managers, who lack empirical evidence to support intervention planning. This may be particularly important on Lesbos. Since the destruction of the Moria camp on 8 September, the situation for refugees on Lesbos has become even more perilous. Refugees lost most of their belongings, including face masks and hand sanitiser, in the fires. More than 9000 people have been relocated to a temporary camp at Kara Tepe,[35 37] but this facility lacks adequate water and sanitation.[37] A new camp is being planned,[35–37] and managers have the opportunity to construct this camp in a way that facilitates future interventions. Beyond Lesbos, our model could be modified to evaluate potential interventions to combat COVID-19 or other infectious diseases in displacement camps or vulnerable populations (eg, urban slums[7]) with different densities, movement patterns or age structures. In all cases, it is important that the interventions chosen be culturally acceptable to the target populations, and this is particularly important when populations have historical reason to distrust authority.[36 40] In general, most interventions are not enforceable, and rely on voluntary compliance by the population. In displaced populations and elsewhere, resistance to planned interventions has sometimes led to low uptake or even violence.[31 32 36 38 41] Therefore, it is imperative that any planned intervention be coupled with an effort to educate the population about the plan, and with clear two-way communication between managers and population members.

Many uncertainties remain about how COVID-19 will affect refugee camp populations, and whether feasible interventions can mitigate these effects. It is not possible to evaluate interventions with well-controlled experiments, because it would be unethical to apply interventions in some populations and withhold them from others. In the absence of empirical data, agent-based simulations like those we present here may offer the best opportunity to assess potential interventions and to plan management strategies that could save human lives.

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Contributors All authors conceptualised the study. RTG built the model and analysed the data, with advice from all authors. SM-S and CH provided information about the Moria refugee camp. All authors wrote the paper.

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Patient consent for publication Not required.

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Data availability statement Data are available in a public, open access repository. Codes used in this study are available at: https://github.com/TuckerGilman/Moria.

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Supplementary Information

S1. Expanded methods

Overview

We developed a spatially explicit agent-based model to simulate COVID-19 epidemics unfolding in a model refugee camp over discrete timesteps that correspond to days. The infection starts in one individual, and is transmitted probabilistically among individuals as they interact during daily activities. We modelled epidemics with no interventions, and epidemics where interventions or combinations of interventions were used to reduce disease transmission. We compared the peak number of infected individuals, the time to peak infection, and the total number of individuals infected, with or without interventions.

The parameter values that describe the population and the camp simulate the Moria refugee camp on Lesbos, Greece. The parameter values that describe disease progression and transmission are drawn from the literature. The parameter values that describe individuals' movements in the camp are heuristic, but our qualitative predictions hold under other reasonable sets of parameter values (supplementary tables S1-S11).

Throughout these methods, we used "Moria" to refer to the Moria refugee camp and "camp" to refer to the camp in our model. We used "person" or "people" to refer to the residents of Moria, and we used "individuals" to refer to individuals in the model population.

The population

The model population comprises 18,700 individuals. Each individual is characterised by its age, sex, condition, and disease state. Condition describes whether an individual is healthy or has a pre-existing condition that increases the risk of severe infection or mortality from COVID-19 (*i.e.*, hypertension, diabetes, cardiovascular disease, or chronic lung disease[2]). Each individual is assigned an age, sex and condition that matches a randomly selected person from the medical records of the Moria camp. These characteristics do not change over time. The disease state describes the progression of a COVID-19 infection in an individual, and therefore does change over time. The initial disease state for all individuals is "susceptible."

The camp

Each individual is a member of a household that occupies either an isobox or a tent. Isoboxes are prefabricated housing units with a mean occupancy of 10 individuals. Tents have a mean occupancy of 4 individuals. A total of 8,100 individuals occupies isoboxes and 10,600 individuals occupy tents. These correspond to the numbers of people that occupied isoboxes and tents in Moria. The exact occupancy of each isobox or tent is drawn from a Poisson distribution, and individuals are assigned to isoboxes or tents randomly without regard to sex or age. This is appropriate because many people arrived at Moria travelling alone, and thus isoboxes or tents may not represent family units.

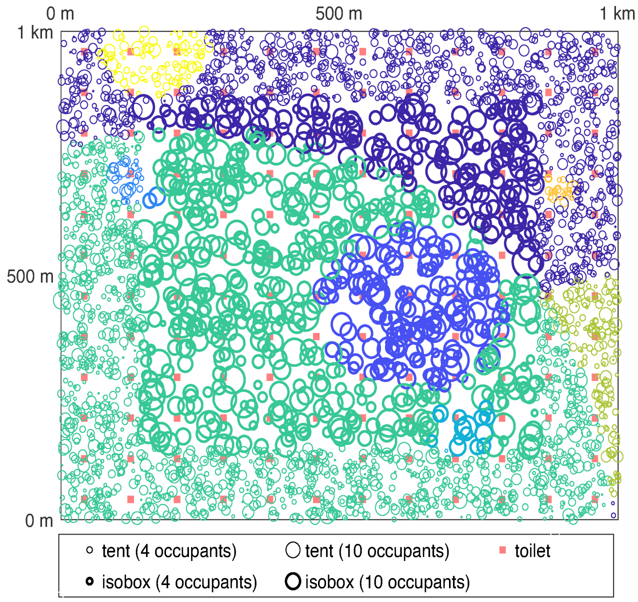

Figure S1.1. A representative example of the camp layout. Circles represent households. Circle size indicates household occupancy and circle colour indicates national or ethinc background. Isoboxes (bold circles) are centrally located, and tents (light circles) are peripherally located. Red squares represent toilets.

The camp covers a 1 x 1 (*e.g.*, km) square (figure S.1.1). Isoboxes are assigned to random locations in a central square that covers one half of the area of the camp. Tents are assigned to random locations in the camp outside of the central square. There are 144 toilets evenly distributed throughout the camp. Toilets are placed at the centres of the squares that form a 12 x 12 grid covering the camp. The camp has one food line. The position of the food line is not explicitly modelled.

In Moria, the homes of people with the same ethnic or national background were spatially clustered, and people interacted more frequently with others from the same background as themselves. To simulate ethnicities or nationalities in our camp, we assigned each household to one of eight "backgrounds" in proportion to the self-reported countries of origin of people in the Moria medical records. For each of the eight simulated backgrounds, we randomly

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selected one tent or isobox to be the seed for the cluster. We assigned the *x* nearest unassigned households to that background, where *x* is the number of households with that background. Thus, the first background occupies an area that is roughly circular, but other backgrounds may occupy less regular shapes (figure S1.1).

Disease Progression

If an individual becomes infected, the infection progresses through a series of disease states (figure S1.2). The time from exposure until symptoms appear (*i.e.*, the incubation period) is drawn from a Weibull distribution with a mean of 6.4 days and a standard deviation of 2.3 days.[19] In the first half of this period, the individual is "exposed" but not infectious. In the second half, the individual is "pre-symptomatic" and infectious.[22] Fractional days are rounded to the nearest whole day in discrete-time simulations. After the incubation period, the individual enters one of two states: "symptomatic" or "1st asymptomatic." Children under the age of 16 become asymptomatic with probability 0.836 and others become asymptomatic with probability 0.178.[21,24] Individuals remain in the symptomatic or 1st asymptomatic states for 5 days and are infectious during this period. After 5 days, individuals pass from the symptomatic to the "mild" or "severe" states with age- and condition-dependent probabilities following Verity and colleagues[26] and Tuite and colleagues[25]. All individuals in the 1st asymptomatic state pass to the "2nd asymptomatic" state. Individuals are infectious in these states. On each day, individuals in the mild or 2nd asymptomatic state pass to the recovered state with probability 0.37,[23] and individuals in the severe state pass to the recovered state with probability 0.071.[20] Recovered individuals are not infectious, and are not susceptible to

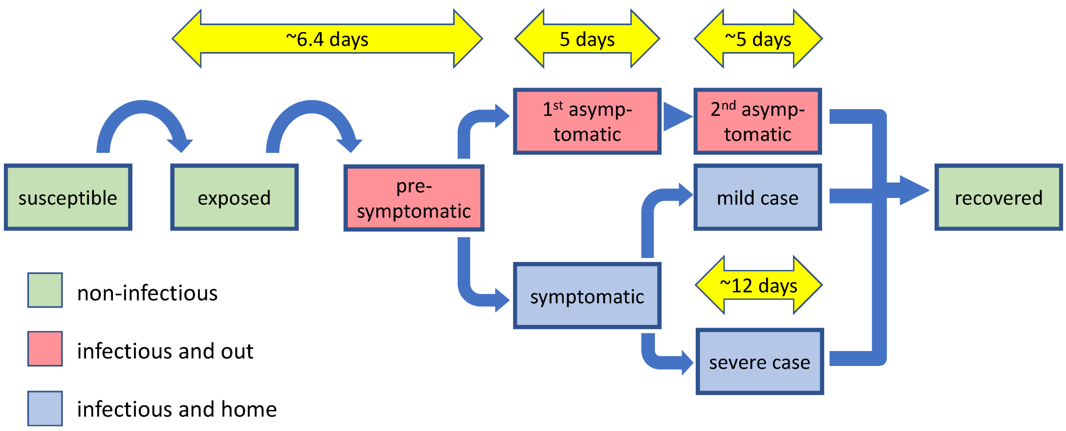

Figure S1.2. Progression of COVID-19 infection in individuals reinfection. We did not model deaths explicitly, but this is unlikely to affect the dynamics of the epidemic if neither recovered nor dead individuals are infectious.

Infection Dynamics

Infection can be transmitted from infectious to susceptible individuals as they go about their daily activities. Let p_{idw} denote the probability that susceptible individual i becomes infected on day d by transmission route w, where $w \in \{h, t, f, m\}$ indicates transmission within the household, at toilets, in the food line, or as individuals move about the camp, respectively. The probability that susceptible individual i becomes infected on day d is thus

$$p_{id} = 1 - \prod_{w \in \{h,t,f,m\}} (1 - p_{idw}). \tag{1}$$

We lack detailed information on how people use space in Moria or any other refugee camp. Therefore, we did not model movement explicitly, but instead calculated the p_{idw}s for each individual given its expected activities on each day. This reduces the computational time for simulations.

Infection within the household. On each day, each infectious individual infects each susceptible individual in the same household with probability p_h. Thus, if individual i shares a household with h_{cid} infectious individuals on day d, then

$$p_{idh} = 1 - (1 - p_h)^{h_{cid}}. \tag{2}$$

Infection at toilets. We assumed that every individual visits the toilet nearest its household 3 times each day, and must always wait in line. If a susceptible individual is in front of or behind an infectious individual in the toilet line, the susceptible individual becomes infected with probability p_t. Thus, the probability that susceptible individual i becomes infected in the toilet line on day d is

$$p_{idt} = 1 - \sum_{j=0}^{6} {6 \choose j} \left(1 - \frac{t_{cid}}{t_{id}}\right)^{6-j} \left(\frac{t_{cid}}{t_{id}}\right)^{j} (1 - p_t)^j, \tag{3}$$

where t_{cid} and t_{id} are the numbers of infectious individuals and of all individuals, respectively, that share a toilet with individual i on day d.

Infection in the food line. The food line forms 3 times each day. We assumed that only individuals without symptoms (*i.e*., susceptible, exposed, pre-symptomatic, asymptomatic, or recovered) attend food lines. Food is delivered to individuals with symptoms by others, without interaction (*e.g*., food might be left outside homes). Each individual without symptoms attends the food line once per day on 3 out of 4 days. On other occasions, food is brought to that individual by another individual without additional interactions. For example, food might be brought by a member of the same household, or by a neighbour with whom the individual would otherwise interact (see below). If an individual attends the food line, it interacts with two individuals behind it and two individuals in front of it in the line. Because food lines in Moria were extremely dense,[13,14] this may be conservative. If a susceptible individual interacts with an infectious individual in the food line, the susceptible individual becomes infected with probability p_f. Thus, the probability that susceptible individual i becomes infected in the food line on day d is

$$p_{idf} = \frac{3}{4}\left(1 - \sum_{j=0}^{4} \binom{4}{j} \left(1 - \frac{n_{yd}}{n_{zd}}\right)^{4-j} \left(\frac{n_{yd}}{n_{zd}}\right)^{j} \left(1 - p_f\right)^{j}\right), \tag{4}$$

where n_{yd} is the number of infectious individuals without symptoms (*i.e*., pre-symptomatic and asymptomatic) in the camp on day d, and n_{zd} is the total number of individuals without symptoms in the camp on day d.

Infection as individuals move about the camp. Individuals move about outside their households, and interact with individuals from other households as they move. We assumed that each individual occupies a circular home range centred on its household, and uses all parts of its home range equally. Two individuals may interact if their home ranges overlap. If individuals i and j have home ranges with radii r_i and r_j, respectively, and the distance between their households is d_{ij}, then the area of overlap in their home ranges is

$$a_{ij} = r_i^2 \operatorname{acos}\left(\frac{d_{ij}^2 + r_i^2 - r_j^2}{2d_{ij}r_i}\right) + r_j^2 \operatorname{acos}\left(\frac{d_{ij}^2 - r_i^2 + r_j^2}{2d_{ij}r_j}\right) - \frac{1}{2}\sqrt{(-d_{ij} + r_i + r_j)(d_{ij} + r_i - r_j)(d_{ij} - r_i + r_j)(d_{ij} + r_i + r_j)}\,. \tag{5}$$

The proportion of time that individuals *i* and *j* spend together in the area of overlap is

$$s_{ij} = \frac{a_{ij}}{\pi r_i^2}\frac{a_{ij}}{\pi r_j^2}\,, \tag{6}$$

and the relative encounter rate between individuals *i* and *j* is

$$\frac{s_{ij}}{a_{ij}} = \frac{a_{ij}}{\pi^2 r_i^2 r_j^2}\,. \tag{7}$$

Equation (7) means that individuals encounter each other more frequently if they co-occupy a small area than if they co-occupy a large area for the same amount of time. To obtain the interaction rate between individuals *i* and *j* from the relative encounter rate, we scaled by a factor g_{ij} to account for ethnicity or country of origin. In particular, $g_{ij} = 1$ if individuals *i* and *j* have the same background, and $g_{ij} = 0.2$ otherwise. Furthermore, we scaled the interaction rate such that two individuals with the same background that share an identical home range with a radius of r_s interact on average once each day. The parameter r_s allows us to scale the mean interaction rate in the population, independent of the area that people occupy outside their homes. After scaling, the daily rate of interaction between individuals *i* and *j* is

$$f_{ij} = r_s^2 \frac{a_{ij}}{\pi r_i^2 r_j^2} g_{ij}\,. \tag{8}$$

We assumed that only individuals without symptoms interact in their home ranges. Thus, the rate at which individual *i* interacts with infected individuals in its home range on day *d* is

$$q_{id} = \sum_j \mathrm{I}(j,d) f_{ij}\,, \tag{9}$$

where $\mathrm{I}(j,d) = 1$ if individual *j* is pre-symptomatic or asymptomatic on day *d* and $\mathrm{I}(j,d) = 0$ otherwise. The summation in equation (9) runs over all individuals in the model that do not share a household with individual i. The probability that susceptible individual i becomes infected on day d while moving about its home range is thus

$$p_{idm} = 1 - e^{-q_{id}p_m}, \tag{10}$$

where p_m is the probability of transmission when a susceptible individual interacts with an infectious individual.

Assigning parameter values. The probabilities that COVID-19 is transmitted among individuals in different settings are not well-understood. Therefore, in the body of this paper we report results for high-transmission (p_h = 0.18, p_t = 0.051, p_f = 0.23, p_m = 0.0085) and low-transmission (p_h = 0.0397, p_t = 0.0067, p_f = 0.0397, p_m = 0.0060) scenarios. These values are derived from the literature[17,18,23,27] in section S2 below. We also know very little about how people use space or interact in Moria or in other refugee camps. Therefore, we modelled high- and low-movement and high- and low-interaction scenarios. In the high-movement scenario, we assumed that males over 10 years old use home ranges with radius 0.2 (*i.e.*, 200 m), and that males under 10 years old and all females use home ranges with radius 0.05. In the low movement scenario, we assumed that males over 10 years old use home ranges with radius 0.1, and all others use home ranges with radius 0.02. In the high-interaction scenario, we set r_s so that the average individual in the camp interacts with 20 others per day (*i.e.*, r_s = 0.0226 and r_s = 0.0202 in high- the low-movement scenarios, respectively). In the low-interaction scenario, we set r_s so that the average individual in the camp interacts with 5 others per day (*i.e.*, r_s = 0.0113 and r_s = 0.0101 in high- the low-movement scenarios, respectively).

For each combination of transmission, movement, and interaction scenario, we estimated the basic reproduction number R_0 by conducting 10^4 simulations. In each simulation, we allowed a randomly selected individual in the population to become infected, and we counted the number of individuals infected by this index case (table S12). In low-transmission scenarios, R_0 ranged from 4.02 to 4.64 depending on the movement and interaction rates. This is slightly higher than in Chinese cities before interventions[28]. In high-transmission scenarios, R_0 ranged from 14.44 to 15.38, in line with estimates from the Diamond Princess before interventions[29]. With shared food lines, shared toilets, and a population density of >20,000 km^{-2}, Moria may have been more similar to a cruise ship than to a city, but with more crowded housing and less sanitation. We believe our low- and high-transmission scenarios represent plausible upper and lower bounds for the transmission potential of COVID-19 in Moria.

Interventions

We modelled four different interventions that might be imposed on the baseline model, alone and in combinations: sectoring, face mask use, remove-and-isolate, and lockdown.

Sectoring. The camp in our baseline model has a single food line where transmission can occur among individuals from any parts of the camp. This facilitates the rapid spread of infection across space. A plausible intervention would be to divide the camp into sectors with separate food lines, and to require individuals to use the food line closest to their homes. This might allow camp managers to contain outbreaks locally. To simulate such an intervention, we divided the camp into n sectors, each with its own food line. These sectors form a $\sqrt{n} \times \sqrt{n}$ grid over the camp. We replaced equation (4) with

$$p_{idf} = \frac{3}{4}\left(1 - \sum_{j=0}^{4} \binom{4}{j} \left(1 - \frac{n_{iyd}}{n_{izd}}\right)^{4-j} \left(\frac{n_{iyd}}{n_{izd}}\right)^{j} \left(1 - \frac{p_f}{\sqrt{n}}\right)^{j}\right). \tag{11}$$

Here n_{iyd} is the number of infectious individuals without symptoms (*i.e.*, pre-symptomatic and asymptomatic) served by the same food line as individual i on day d, and n_{izd} is the total number of individuals without symptoms served by the same food line as individual i on day d. Rescaling the transmission probability by $1/\sqrt{n}$ accounts for the fact that shorter lines have shorter waiting times. We conducted simulations with $n \in \{4, 16, 144\}$ to study how the number of sectors might affect COVID-19 epidemics.

Face mask use. Behavioral changes such as using personal protective equipment, frequent handwashing, and maintaining safe distances from others may reduce the risk of COVID-19 transmission. In Moria, there was approximately one tap per 42 people, so frequent handwashing (*e.g.*, greater than 10x per day, as in[30]) was impossible. Due to the high population density, maintaining safe distances from others was also difficult or impossible.[5] However, people in Moria were provided with face masks, and healthcare workers in the camp report that these were widely used. To simulate the use of face masks, we scaled the

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odds of transmission per interaction in food lines, in toilet lines, and during movement about the camp by a factor of 0.32 following Jefferson and colleagues.[30]

Remove-and-isolate. Managers of some populations, including Moria, have planned interventions in which people with COVID-19 infections and their households are to be removed from populations and kept in isolation until the infected people have recovered. By isolating entire households, managers aim to remove asymptomatic and pre-symptomatic individuals from the population, and to ensure that carers are not separated from their families. To simulate a remove-and-isolate intervention, we conducted simulations in which in each individual with symptoms (*i.e*., symptomatic, mild case, or severe case) is detected with probability b on each day. If an individual with symptoms is detected, that individual and its household are removed from the camp. Individuals removed from the camp can infect or become infected by others in their households following equation (2), but cannot infect or become infected by individuals in other households by any transmission route. We assumed that individuals are returned to the camp 7 days after they have recovered, or if they do not become infected, 7 days after the last infected person in their household has recovered. We simulated remove-and-isolate interventions with $b \in \{1, 0.5, 0.25\}$. These capture interventions in which symptomatic individuals and their households are removed on average on the 1st, 2nd, or 4th day of symptoms.

Lockdown. Some countries have attempted to limit the spread of COVID-19 by requiring people to stay in or close to their homes.[11] This intervention has sometimes been called "lockdown." We simulated lockdowns in which most individuals are restricted to home ranges with radius r_l around their households, except when visiting shared toilets or food lines. We assumed that a proportion v_l of the population violates the lockdown. Thus, for each individual in the population, we set their home range to r_l with probability (1- v_l). Otherwise, we set their home range to 0.2 in the high-movement scenario or to 0.1 in the low movement scenario. We simulated interventions with $(r_l, v_l) \in \{(0.005, 0.05), (0.01, 0.1), (0.02, 0.2)\}$ to study lockdowns that are more or less restrictive and strictly enforced.

Simulations

In each simulation, we initialised the model population and camp structure as described above, and we randomly selected one individual to enter the exposed state. We simulated the epidemic by iterating days, and we tracked the disease state of each individual over time. We ran each simulation until all individuals in the population were either susceptible or recovered, at which point the epidemic had ended. If fewer than 20 individuals became infected, we recorded that an epidemic had been averted. If the epidemic was not averted, then we recorded the maximum number of infected individuals, the time to peak infection, and the proportion of the population that became infected in each simulation. For remove-and-isolate interventions, we also recorded the peak number of individuals in isolation to assess feasibility.

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S2. Estimating transmission probabilities for the high- and low-transmission scenarios

High-transmission scenarios

For the initial high-transmission scenario (HT1), we estimated the daily transmission probability within households, p_h, using data from Danis and colleagues.[27] Danis and colleagues reported that 8 of 10 people who shared an apartment in a French chalet for four days with one infectious individual subsequently became infected. Thus, we estimated $p_h = 0.33$ by solving $1 - (1 - p_h)^4 = 8/10$.

We estimated transmission rates per interaction using data from Liu and colleagues.[23] Liu and colleagues reported a total of 43 secondary infections among 126 attendees at 8 meals, each with one infectious individual present. We assumed that meals lasted 2 h and that the transmission rate was constant over time. Thus, the probability of transmission in an interaction lasting m minutes is

$$p(m) = 1 - \left(1 - \frac{43}{126}\right)^{\frac{m}{120}}.$$

We assumed that interactions in food lines, toilet lines, and while moving about the camp lasted for 150 min, 30 min, and 5 min respectively. Therefore, $p_f = p(150) = 0.407$, $p_t = p(30) = 0.099$, and $p_f = p(5) = 0.017$.

The transmission parameters in HT1 result in R_0s in that range from 22.1 to 23.8 depending on the movement and interaction rates in the model population. These are higher than have been observed for COVID-19 in any real population. It is possible that the data reported by Danis and colleagues and Liu and colleagues represent rare, so-called "super-spreader" events. Therefore, we created a second high-transmission scenario (HT2) in which we reduced the rate of transmission in each transmission route by a factor of 0.5. Thus,

$$p_{i,HT2} = 1 - \left(1 - p_{i,HT1}\right)^{1/2},$$

where $p_{i,HT1}$ and $p_{i,HT2}$ are the transmission probabilities for transmission route i in high-transmission scenarios HT1 and HT2, respectively. In HT2, $p_h = 0.18$, $p_f = 0.23$, $p_t = 0.051$,

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and $p_f = 0.0085$. Without interventions R_0 in HT2 ranges from 14.44 to 15.38, in line with estimates from the Diamond Princess before interventions.[29] In the body of this paper, we present results from HT2. Results from HT1 are presented in supplementary tables S1-S12.

Low-transmission scenarios

For the initial low-transmission scenario (LT1), we estimated the daily transmission probability within households using data from Li and colleagues.[17] Li and colleagues studied the households of 105 COVID-19 patients who were hospitalised in China between 1 January and 20 February 2020. Household members were exposed to infection until patients were hospitalised, and Li and colleagues recorded the proportion of household members that became infected.

Members of households occupying isoboxes or tents in the Moria refugee camp may have been in closer contact for longer periods than members of Chinese households. Therefore, we assumed that the transmission rates among household members in Moria would be similar to the transmission rates between spouses in Chinese households, who may be in closer contact than other household members.

Li and colleagues reported that 25 of 90 spouses of infectious individuals became infected. However, spouses in Li and colleagues' data were exposed to their infectious partners for multiple days, and our model is parameterised on daily transmission probabilities. Therefore, we estimated the days of exposure for spouses in Li and colleagues' data set, and used this and the total infection rate to estimate the daily transmission probability. Li and colleagues reported that 12 patients were hospitalised on days 0 or 1 of symptoms, 34 were hospitalised on days 2-5 of symptoms, and 59 were hospitalised on days 7-11 of symptoms. Fourteen patients self-isolated in their homes from the onset of symptoms and there was no transmission from these patients to their households. We do not know on which days the patients that self-isolated were hospitalised, so we assumed that they were divided proportionally between the group that was hospitalised on days 2-5 and the group that was hospitalised on days 7-11. We assumed that every patient became infectious three days before the appearance of symptoms[22] and remained infections until hospitalisation. We do not know the exact day on which patients were hospitalised, so we assumed that all patients were hospitalised on the middle day for their groups. We solved

$$\frac{12(1-(1-p_h)^{3.5}) + 14(1-(1-p_h)^{3}) + 34\frac{79}{93}(1-(1-p_h)^{6.5}) + 59\frac{79}{93}(1-(1-p_h)^{12})}{105} = \frac{25}{90}$$

for p_h to obtain an estimated daily transmission probability within households of 0.0397. Because the Moria population had smaller homes, less sanitary conditions (*e.g.*, no washing facilities in homes), and poorer background health than the population Li and colleagues studied, this estimate may be conservative.

We set the transmission probability between individuals that interact in food lines, p_f, equal to p_h. This is reasonable because food lines in Moria were dense and people waited in food lines for up to 3 h per visit.[13,14] We set the transmission probability between individuals that interact in toilet lines to $1 - (1 - p_f)^{1/6} = 0.0067$ to reflect an estimated 30 min waiting time in toilet lines. We set the transmission rate per interaction during movement in the camp to $p_m = 0.006$ following Shen and colleagues.[18] Shen and colleagues reported that 3 of 473 of attendees at three parties with 2 infectious individuals became infected. It is unlikely that the 2 infectious individuals interacted with all of the other attendees at each party. Thus, Shen and colleagues' estimate may be conservative as a per-interaction transmission probability.

The transmission parameters in LT1 result in R_0s in that range from 4.02 to 4.64, slightly higher than those observed in Chinese cities before interventions.[28] This is plausible because conditions in Moria were likely to have favoured transmission more than those in Chinese cities.

Because they are estimated from different sources, the relative rates of transmission among transmission routes (*e.g.*, transmission in toilet lines relative to transmission in casual interactions during daily activities) differ between LT1 and the high-transmission scenarios. To show that differences between our high- and low-transmission scenarios are due to overall transmission and not to differences in the relative transmission rates among transmission routes, we created a second low-transmission scenario (LT2) by rescaling the transmission rates in HT1. In particular, we set

$$p_{i,LT2} = 1 - \left(1 - p_{i,HT1}\right)^{1/10}.$$

Thus, in LT2, $p_h = 0.039$, $p_f = 0.051$, $p_t = 0.010$, and $p_f = 0.0017$, and without interventions R_0 ranges from 4.32 to 4.51 depending on the movement and interaction rates in the model population.

In the body of this paper, we report results for LT1. Figure S2.1 shows that the qualitative results presented in figures 3 and 4 also hold under LT2.

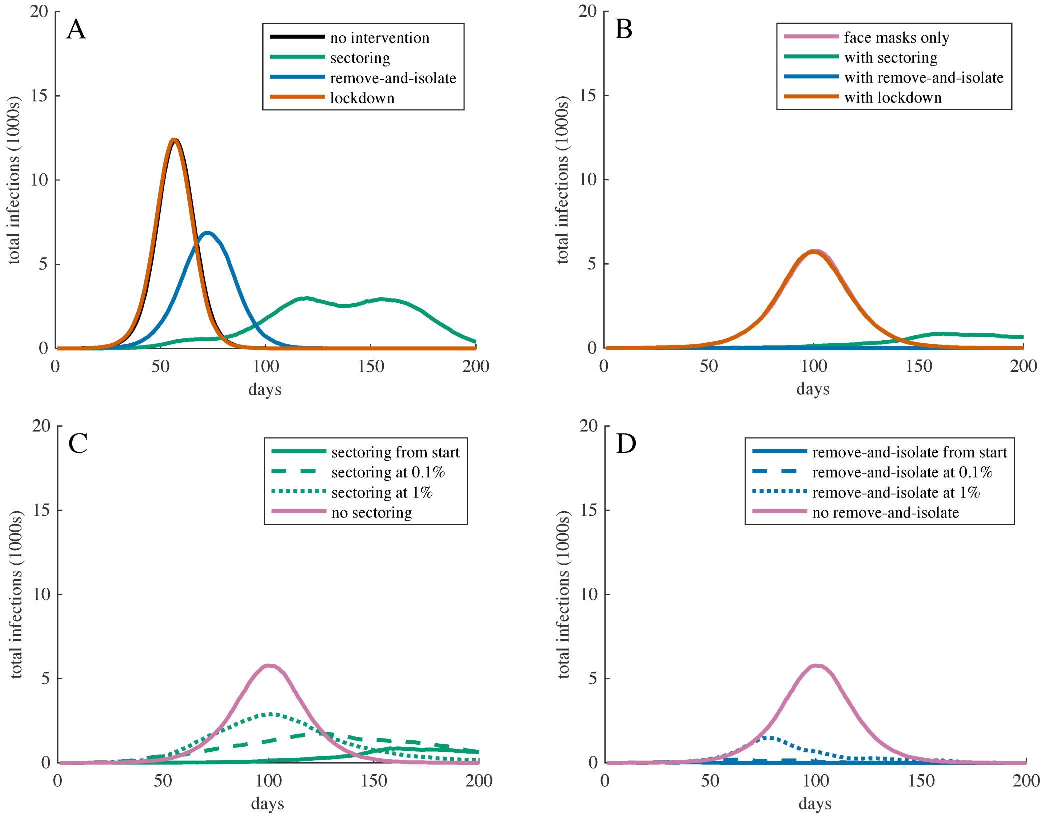

Figure S2.1. Total infections over time for COVID-19 epidemics with different interventions in populations with low movement, high interaction rates, and low transmission (LT2) probabilities. Intervention intensities are as in figures 3 and 4. Curves show the most representative simulation (*i.e.*, the simulation with the peak infection and peak infection date closest to the median) for the corresponding intervention. (A) shows the effect of each intervention alone (compare to figure 3A). (B) shows the effect of each intervention when face masks are also in use (compare to figure 3C). (C) shows the effect of sectoring beginning after infection is detected in the camp (compare to figure 4A). (D) shows the effect of remove-and-isolate beginning after infection has been detected in the camp (compare to figure 4C).

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Supplementary Tables

Supplementary tables S1-S11 report summary statistics for COVID-19 introductions into the model population in scenarios without (S1) or with (S2-S11) interventions. Each row represents 200 simulations. The peak and total proportions of individuals infected, time to peak infection, and peak population in isolation are reported as medians with interquartile ranges. Epidemics adverted is the proportion of simulations in which fewer than 20 individuals became infected. Transmission probabilities for the low- and high-transmission scenarios, and assumptions of the low- and high-movement and low- and high-interaction scenarios, are presented in the supplementary information. Rows highlighted in pink represent the scenarios reported in the body of the paper.

Table S1

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
No intervention	Low (LT1)	Low	Low	0.57 (0.57-0.58)	64 (60-70)	0.97 (0.97-0.97)	0.05	
			High	0.67 (0.66-0.67)	55 (52-59)	0.98 (0.98-0.98)	0.03	
		High	Low	0.58 (0.57-0.58)	65 (61-71)	0.97 (0.97-0.97)	0.05	
			High	0.68 (0.67-0.68)	55 (51-59)	0.98 (0.98-0.98)	0.02	
	High (HT2)	Low	Low	0.98 (0.98-0.98)	27 (25-27)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	25 (25-27)	>0.99	<0.01	
		High	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (25-27)	>0.99	<0.01	
	High (HT1)	Low	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (19-21)	>0.99	<0.01	
		High	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (19-21)	>0.99	<0.01	

Table S2

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
Face masks	Low (LT1)	Low	Low	0.23 (0.22-0.23)	119 (111-129)	0.80 (0.80-0.81)	0.22	
			High	0.31 (0.31-0.32)	96 (89-106)	0.87 (0.87-0.88)	0.17	
		High	Low	0.23 (0.23-0.24)	116 (108-126)	0.80 (0.80-0.81)	0.21	
			High	0.32 (0.32-0.33)	92 (84-101)	0.87 (0.87-0.88)	0.20	
	High (HT2)	Low	Low	0.88 (0.88-0.89)	37 (35-39)	>0.99	<0.01	
			High	0.90 (0.89-0.90)	36 (34-38)	>0.99	<0.01	
		High	Low	0.89 (0.88-0.89)	37 (36-39)	>0.99	<0.01	
			High	0.90 (0.90-0.90)	35 (34-37)	>0.99	<0.01	
	High (HT1)	Low	Low	0.97 (0.97-0.97)	27 (26-29)	>0.99	<0.01	
			High	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	
		High	Low	0.97 (0.97-0.97)	27 (26-29)	>0.99	<0.01	
			High	0.97 (0.97-0.98)	26 (25-28)	>0.99	<0.01	

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Table S3

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
4 sectors	Low (LT1)	Low	Low	0.25 (0.24-0.27)	103 (95-111)	0.94 (0.94-0.94)	0.08	
			High	0.34 (0.32-0.37)	78 (73-84)	0.97 (0.97-0.97)	0.08	
		High	Low	0.30 (0.28-0.32)	91 (83-101)	0.94 (0.94-0.94)	0.07	
			High	0.43 (0.40-0.46)	68 (62-73)	0.97 (0.97-0.97)	0.05	
	High (HT2)	Low	Low	0.60 (0.54-0.66)	43 (40-45)	>0.99	<0.01	
			High	0.67 (0.65-0.71)	38 (35-40)	>0.99	<0.01	
		High	Low	0.68 (0.64-0.73)	40 (37-42)	>0.99	<0.01	
			High	0.79 (0.76-0.83)	34 (33-36)	>0.99	<0.01	
	High (HT1)	Low	Low	0.73 (0.68-0.77)	33 (32-36)	>0.99	<0.01	
			High	0.83 (0.79-0.86)	30 (28-31)	>0.99	<0.01	
		High	Low	0.83 (0.78-0.86)	31 (29-32)	>0.99	<0.01	
			High	0.91 (0.89-0.93)	27 (26-28)	>0.99	<0.01	
16 sectors	Low (LT1)	Low	Low	0.13 (0.13-0.15)	138 (117-158)	0.91 (0.91-0.91)	0.07	
			High	0.20 (0.19-0.22)	98 (86-111)	0.96 (0.96-0.96)	0.05	
		High	Low	0.18 (0.17-0.20)	108 (95-127)	0.91 (0.91-0.91)	0.10	
			High	0.31 (0.28-0.34)	73 (68-84)	0.96 (0.96-0.96)	0.05	
	High (HT2)	Low	Low	0.34 (0.32-0.39)	61 (54-70)	>0.99	<0.01	
			High	0.41 (0.39-0.47)	51 (45-57)	>0.99	<0.01	
		High	Low	0.43 (0.40-0.49)	50 (46-59)	>0.99	<0.01	
			High	0.55 (0.52-0.62)	43 (38-47)	>0.99	<0.01	
	High (HT1)	Low	Low	0.45 (0.43-0.52)	46 (41-53)	>0.99	<0.01	
			High	0.54 (0.51-0.62)	40 (35-44)	>0.99	<0.01	
		High	Low	0.55 (0.53-0.62)	39 (36-44)	>0.99	<0.01	
			High	0.71 (0.67-0.77)	34 (31-36)	>0.99	<0.01	
144 sectors	Low (LT1)	Low	Low	0.08 (0.07-0.09)	210 (173-252)	0.88 (0.88-0.88)	0.14	
			High	0.15 (0.14-0.17)	113 (98-136)	0.95 (0.95-0.96)	0.06	
		High	Low	0.14 (0.13-0.15)	130 (111-162)	0.88 (0.88-0.89)	0.10	
			High	0.27 (0.26-0.30)	78 (71-91)	0.95 (0.95-0.95)	0.06	
	High (HT2)	Low	Low	0.19 (0.17-0.21)	101 (82-119)	>0.99	<0.01	
			High	0.27 (0.26-0.30)	68 (58-79)	>0.99	<0.01	
		High	Low	0.33 (0.30-0.36)	64 (57-75)	>0.99	<0.01	
			High	0.48 (0.45-0.53)	47 (42-51)	>0.99	<0.01	
	High (HT1)	Low	Low	0.26 (0.24-0.29)	73 (60-82)	>0.99	<0.01	
			High	0.36 (0.34-0.41)	53 (44-60)	>0.99	<0.01	
		High	Low	0.46 (0.42-0.50)	47 (43-53)	>0.99	<0.01	
			High	0.62 (0.59-0.67)	37 (34-41)	>0.99	<0.01	

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Table S4

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
Remove and isolate on ~day 4	Low (LT1)	Low	Low	0.31 (0.30-0.32)	84 (79-91)	0.83 (0.83-0.84)	0.28	0.43 (0.42-0.44)
			High	0.46 (0.45-0.47)	65 (61-70)	0.90 (0.90-0.90)	0.20	0.59 (0.58-0.60)
		High	Low	0.31 (0.30-0.33)	82 (77-90)	0.83 (0.83-0.84)	0.26	0.43 (0.42-0.45)
			High	0.47 (0.46-0.48)	62 (58-67)	0.90 (0.90-0.90)	0.17	0.60 (0.59-0.61)
	High (HT2)	Low	Low	0.97 (0.96-0.97)	28 (27-29)	>0.99	<0.01	0.92 (0.92-0.92)
			High	0.97 (0.97-0.97)	27 (26-28)	>0.99	0.02	0.93 (0.92-0.93)
		High	Low	0.97 (0.97-0.97)	27 (26-29)	>0.99	<0.01	0.92 (0.92-0.92)
			High	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	0.93 (0.93-0.93)
	High (HT1)	Low	Low	>0.99	21 (20-22)	>0.99	<0.01	0.95 (0.95-0.95)
			High	>0.99	21 (20-22)	>0.99	<0.01	0.95 (0.95-0.95)
		High	Low	>0.99	22 (21-22)	>0.99	<0.01	0.95 (0.94-0.95)
			High	>0.99	21 (20-22)	>0.99	<0.01	0.95 (0.95-0.95)
Remove and isolate on ~day 2	Low (LT1)	Low	Low	0.23 (0.22-0.24)	94 (85-104)	0.77 (0.76-0.78)	0.43	0.36 (0.34-0.38)
			High	0.39 (0.38-0.40)	70 (65-76)	0.87 (0.86-0.87)	0.27	0.57 (0.55-0.58)
		High	Low	0.23 (0.22-0.24)	92 (83-103)	0.77 (0.76-0.78)	0.43	0.36 (0.34-0.38)
			High	0.41 (0.40-0.42)	66 (62-72)	0.87 (0.87-0.87)	0.24	0.58 (0.57-0.59)
	High (HT2)	Low	Low	0.96 (0.96-0.96)	29 (27-30)	>0.99	0.01	0.95 (0.94-0.95)
			High	0.97 (0.96-0.97)	27 (26-29)	>0.99	0.02	0.95 (0.95-0.95)
		High	Low	0.96 (0.96-0.96)	28 (27-29)	>0.99	<0.01	0.95 (0.94-0.95)
			High	0.97 (0.97-0.97)	27 (26-28)	>0.99	0.02	0.95 (0.95-0.95)
	High (HT1)	Low	Low	>0.99	22 (21-23)	>0.99	<0.01	0.97 (0.97-0.97)
			High	>0.99	21 (20-22)	>0.99	<0.01	0.97 (0.97-0.97)
		High	Low	>0.99	22 (21-23)	>0.99	<0.01	0.97 (0.97-0.97)
			High	>0.99	21 (20-22)	>0.99	<0.01	0.97 (0.97-0.97)
Remove and isolate on ~day 1	Low (LT1)	Low	Low	0.18 (0.16-0.20)	104 (93-111)	0.71 (0.70-0.73)	0.40	0.30 (0.27-0.32)
			High	0.35 (0.34-0.36)	72 (67-81)	0.85 (0.84-0.85)	0.40	0.54 (0.52-0.54)
		High	Low	0.19 (0.17-0.20)	102 (91-110)	0.72 (0.70-0.73)	0.47	0.31 (0.28-0.33)
			High	0.36 (0.35-0.37)	68 (63-76)	0.85 (0.84-0.85)	0.32	0.56 (0.54-0.57)
	High (HT2)	Low	Low	0.95 (0.95-0.95)	29 (28-31)	>0.99	0.01	0.95 (0.95-0.95)
			High	0.96 (0.96-0.96)	28 (27-29)	>0.99	0.01	0.96 (0.96-0.96)
		High	Low	0.95 (0.95-0.95)	29 (28-30)	>0.99	<0.01	0.95 (0.95-0.95)
			High	0.96 (0.96-0.96)	28 (27-29)	>0.99	<0.01	0.96 (0.96-0.96)
	High (HT1)	Low	Low	>0.99	22 (21-23)	>0.99	<0.01	0.97 (0.97-0.97)
			High	>0.99	21 (21-22)	>0.99	<0.01	0.98 (0.97-0.98)
		High	Low	>0.99	22 (21-23)	>0.99	<0.01	0.97 (0.97-0.98)
			High	>0.99	21 (20-22)	>0.99	<0.01	0.98 (0.97-0.97)

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Table S5

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
Loose lockdown	Low (LT1)	Low	Low	0.58 (0.57-0.58)	65 (61-69)	0.97 (0.97-0.97)	0.02	
			High	0.67 (0.67-0.68)	55 (53-60)	0.99 (0.98-0.99)	0.02	
		High	Low	0.58 (0.58-0.59)	64 (61-67)	0.97 (0.97-0.97)	0.06	
			High	0.69 (0.68-0.69)	54 (52-58)	0.99 (0.99-0.99)	0.03	
	High (HT2)	Low	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (25-27)	>0.99	<0.01	
		High	Low	0.98 (0.98-0.98)	27 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	25 (24-27)	>0.99	<0.01	
	High (HT1)	Low	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (19-21)	>0.99	<0.01	
		High	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (19-21)	>0.99	<0.01	
Moderate lockdown	Low (LT1)	Low	Low	0.57 (0.57-0.58)	65 (61-68)	0.97 (0.97-0.97)	0.04	
			High	0.66 (0.65-0.66)	57 (54-61)	0.98 (0.98-0.99)	0.04	
		High	Low	0.58 (0.58-0.59)	64 (61-68)	0.97 (0.97-0.97)	0.06	
			High	0.68 (0.67-0.68)	55 (53-59)	0.99 (0.99-0.99)	0.02	
	High (HT2)	Low	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (25-27)	>0.99	<0.01	
		High	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (24-27)	>0.99	<0.01	
	High (HT1)	Low	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (20-21)	>0.99	<0.01	
		High	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	20 (19-21)	>0.99	<0.01	
Tight lockdown	Low (LT1)	Low	Low	0.57 (0.56-0.57)	66 (63-70)	0.97 (0.97-0.97)	0.06	
			High	0.63 (0.62-0.63)	59 (56-63)	0.98 (0.98-0.98)	0.04	
		High	Low	0.58 (0.57-0.58)	66 (63-71)	0.97 (0.97-0.97)	0.04	
			High	0.64 (0.63-0.64)	58 (55-63)	0.98 (0.98-0.98)	0.02	
	High (HT2)	Low	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (25-27)	>0.99	<0.01	
		High	Low	0.98 (0.98-0.98)	26 (25-28)	>0.99	<0.01	
			High	0.98 (0.98-0.98)	26 (25-27)	>0.99	<0.01	
	High (HT1)	Low	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	21 (20-22)	>0.99	<0.01	
		High	Low	>0.99	21 (20-22)	>0.99	<0.01	
			High	>0.99	21 (20-21)	>0.99	<0.01	

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Table S6

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
4 sectors with face masks	Low (LT1)	Low	Low	0.073 (0.067-0.084)	217 (190-244)	0.68 (0.68-0.69)	0.37	
			High	0.14 (0.13-0.15)	145 (130-165)	0.82 (0.82-0.82)	0.23	
		High	Low	0.098 (0.088-0.11)	180 (159-198)	0.68 (0.68-0.69)	0.31	
			High	0.19 (0.18-0.21)	119 (106-133)	0.82 (0.82-0.83)	0.22	
	High (HT2)	Low	Low	0.41 (0.39-0.44)	62 (59-65)	>0.99	<0.01	
			High	0.48 (0.45-0.52)	55 (51-58)	>0.99	<0.01	
		High	Low	0.49 (0.46-0.55)	59 (56-62)	>0.99	<0.01	
			High	0.58 (0.55-0.62)	50 (47-53)	>0.99	<0.01	
	High (HT1)	Low	Low	0.53 (0.50-0.61)	45 (42-47)	>0.99	<0.01	
			High	0.65 (0.61-0.70)	39 (36-42)	>0.99	<0.01	
		High	Low	0.66 (0.61-0.70)	41 (39-44)	>0.99	<0.01	
			High	0.75 (0.72-0.78)	36 (34-38)	>0.99	<0.01	
16 sectors with face masks	Low (LT1)	Low	Low	0.037 (0.030-0.043)	277 (195-341)	0.50 (0.47-0.52)	0.42	
			High	0.090 (0.082-0.10)	167 (137-207)	0.77 (0.76-0.78)	0.26	
		High	Low	0.054 (0.049-0.060)	199 (166-247)	0.54 (0.53-0.56)	0.42	
			High	0.13 (0.13-0.14)	129 (108-149)	0.78 (0.77-0.78)	0.25	
	High (HT2)	Low	Low	0.22 (0.21-0.25)	92 (81-110)	>0.99	<0.01	
			High	0.28 (0.26-0.30)	76 (66-84)	>0.99	0.01	
		High	Low	0.27 (0.25-0.31)	80 (71-92)	>0.99	<0.01	
			High	0.36 (0.34-0.39)	62 (55-70)	>0.99	<0.01	
	High (HT1)	Low	Low	0.32 (0.29-0.36)	65 (58-76)	>0.99	<0.01	
			High	0.39 (0.36-0.42)	53 (48-62)	>0.99	<0.01	
		High	Low	0.39 (0.37-0.43)	53 (48-64)	>0.99	<0.01	
			High	0.51 (0.48-0.57)	44 (40-50)	>0.99	<0.01	
144 sectors with face masks	Low (LT1)	Low	Low	0.009 (0.002-0.014)	177 (91-294)	0.15 (0.01-0.23)	0.60	
			High	0.063 (0.056-0.068)	218 (176-260)	0.71 (0.70-0.72)	0.28	
		High	Low	0.032 (0.025-0.035)	228 (164-288)	0.38 (0.34-0.40)	0.60	
			High	0.11 (0.11-0.12)	135 (114-166)	0.73 (0.72-0.74)	0.29	
	High (HT2)	Low	Low	0.11 (0.10-0.12)	174 (143-208)	0.99 (0.98-0.99)	<0.01	
			High	0.17 (0.16-0.19)	106 (87-126)	>0.99	<0.01	
		High	Low	0.19 (0.17-0.21)	103 (89-121)	>0.99	0.01	
			High	0.31 (0.38-0.34)	71 (61-80)	>0.99	<0.01	
	High (HT1)	Low	Low	0.17 (0.15-0.19)	108 (92-130)	>0.99	<0.01	
			High	0.25 (0.23-0.27)	76 (62-88)	>0.99	<0.01	
		High	Low	0.29 (0.26-0.32)	70 (62-84)	>0.99	<0.01	
			High	0.43 (0.40-0.47)	51 (45-58)	>0.99	<0.01	

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Table S7

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epid'ics averted	Peak population in isolation
Remove and isolate on ~day 4 with face masks	Low (LT1)	Low	Low	0.002 (0.001-0.003)	44 (33-62)	0.005 (0.003-0.011)	0.76	0.002 (0.002-0.005)
			High	0.010 (0.002-0.026)	87 (36-169)	0.064 (0.005-0.28)	0.60	0.016 (0.003-0.039)
		High	Low	0.002 (0.001-0.002)	33 (26-47)	0.004 (0.002-0.006)	0.76	0.003 (0.002-0.004)
			High	0.016 (0.003-0.032)	124 (48-189)	0.20 (0.008-0.32)	0.66	0.026 (0.004-0.048)
	High (HT2)	Low	Low	0.82 (0.81-0.82)	41 (40-43)	>0.99	0.06	0.81 (0.81-0.82)
			High	0.84 (0.83-0.84)	40 (38-41)	>0.99	0.06	0.83 (0.83-0.83)
		High	Low	0.82 (0.81-0.82)	41 (39-43)	>0.99	0.08	0.81 (0.81-0.82)
			High	0.84 (0.84-0.84)	39 (38-42)	>0.99	0.06	0.83 (0.83-0.83)
	High (HT1)	Low	Low	0.96 (0.96-0.96)	29 (28-30)	>0.99	0.03	0.91 (0.91-0.91)
			High	0.96 (0.96-0.96)	28 (27-29)	>0.99	<0.01	0.92 (0.92-0.92)
		High	Low	0.96 (0.96-0.96)	29 (28-30)	>0.99	<0.01	0.91 (0.91-0.91)
			High	0.96 (0.96-0.96)	28 (27-29)	>0.99	0.02	0.92 (0.92-0.92)
Remove and isolate on ~day 2 with face masks	Low (LT1)	Low	Low	0.002 (0.001-0.002)	34 (26-46)	0.003 (0.002-0.005)	0.82	0.003 (0.002-0.004)
			High	0.002 (0.002-0.004)	35 (26-56)	0.006 (0.003-0.013)	0.66	0.004 (0.002-0.006)
		High	Low	0.002 (0.001-0.003)	32 (25-42)	0.003 (0.002-0.006)	0.83	0.002 (0.002-0.004)
			High	0.002 (0.002-0.007)	40 (29-77)	0.006 (0.002-0.029)	0.68	0.004 (0.002-0.011)
	High (HT2)	Low	Low	0.78 (0.77-0.78)	44 (42-46)	>0.99	0.06	0.82 (0.82-0.83)
			High	0.80 (0.80-0.81)	42 (40-45)	>0.99	0.06	0.84 (0.84-0.85)
		High	Low	0.78 (0.77-0.78)	44 (42-46)	>0.99	0.10	0.82 (0.82-0.83)
			High	0.80 (0.80-0.81)	41 (39-43)	>0.99	0.08	0.84 (0.84-0.84)
	High (HT1)	Low	Low	0.95 (0.95-0.95)	30 (29-31)	>0.99	0.02	0.94 (0.93-0.94)
			High	0.96 (0.95-0.96)	29 (28-30)	>0.99	0.01	0.94 (0.94-0.94)
		High	Low	0.95 (0.95-0.95)	29 (28-30)	>0.99	0.04	0.94 (0.93-0.94)
			High	0.96 (0.95-0.96)	28 (27-30)	>0.99	0.02	0.94 (0.94-0.94)
Remove and isolate on ~day 1 with face masks	Low (LT1)	Low	Low	0.001 (0.001-0.002)	27 (20-33)	0.002 (0.002-0.004)	0.84	0.002 (0.002-0.003)
			High	0.003 (0.002-0.004)	45 (29-62)	0.006 (0.002-0.014)	0.80	0.004 (0.002-0.008)
		High	Low	0.002 (0.001-0.002)	30 (24-34)	0.003 (0.002-0.004)	0.86	0.002 (0.002-0.003)
			High	0.002 (0.001-0.004)	34 (21-53)	0.004 (0.002-0.009)	0.77	0.003 (0.002-0.006)
	High (HT2)	Low	Low	0.73 (0.72-0.74)	46 (44-50)	>0.99	0.13	0.81 (0.80-0.81)
			High	0.76 (0.76-0.77)	44 (42-47)	>0.99	0.10	0.83 (0.82-0.84)
		High	Low	0.73 (0.73-0.74)	47 (44-50)	>0.99	0.10	0.81 (0.80-0.81)
			High	0.76 (0.76-0.77)	44 (41-47)	>0.99	0.10	0.83 (0.83-0.84)
	High (HT1)	Low	Low	0.94 (0.94-0.94)	30 (29-32)	>0.99	0.01	0.94 (0.94-0.94)
			High	0.95 (0.95-0.95)	29 (28-31)	>0.99	0.02	0.95 (0.95-0.95)
		High	Low	0.94 (0.94-0.94)	31 (30-32)	>0.99	0.01	0.94 (0.94-0.94)
			High	0.95 (0.95-0.95)	29 (28-31)	>0.99	0.02	0.95 (0.95-0.95)

Table S8

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
Loose lockdown with face masks	Low (LT1)	Low	Low	0.23 (0.22-0.23)	120 (110-132)	0.80 (0.80-0.81)	0.24	
			High	0.31 (0.31-0.32)	97 (90-104)	0.88 (0.87-0.88)	0.14	
		High	Low	0.23 (0.23-0.24)	119 (108-129)	0.81 (0.81-0.82)	0.22	
			High	0.33 (0.32-0.33)	95 (87-104)	0.89 (0.88-0.89)	0.14	
	High (HT2)	Low	Low	0.89 (0.88-0.89)	37 (35-39)	>0.99	<0.01	
			High	0.90 (0.89-0.90)	36 (34-37)	>0.99	<0.01	
		High	Low	0.89 (0.88-0.89)	37 (35-39)	>0.99	<0.01	
			High	0.90 (0.90-0.90)	36 (34-37)	>0.99	<0.01	
	High (HT1)	Low	Low	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	
			High	0.97 (0.97-0.97)	27 (25-28)	>0.99	<0.01	
		High	Low	0.97 (0.97-0.97)	27 (26-29)	>0.99	<0.01	
			High	0.97 (0.97-0.98)	26 (25-28)	>0.99	<0.01	
Moderate lockdown with face masks	Low (LT1)	Low	Low	0.22 (0.22-0.23)	122 (112-135)	0.80 (0.80-0.81)	0.19	
			High	0.30 (0.29-0.30)	102 (95-112)	0.87 (0.87-0.88)	0.14	
		High	Low	0.23 (0.22-0.24)	118 (108-125)	0.81 (0.81-0.82)	0.22	
			High	0.31 (0.31-0.32)	99 (92-108)	0.88 (0.88-0.89)	0.14	
	High (HT2)	Low	Low	0.89 (0.88-0.89)	37 (36-39)	>0.99	<0.01	
			High	0.90 (0.89-0.90)	36 (34-37)	>0.99	<0.01	
		High	Low	0.89 (0.88-0.89)	37 (35-39)	>0.99	<0.01	
			High	0.90 (0.90-0.90)	36 (34-38)	>0.99	<0.01	
	High (HT1)	Low	Low	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	
			High	0.97 (0.97-0.97)	26 (26-28)	>0.99	<0.01	
		High	Low	0.97 (0.97-0.97)	28 (26-29)	>0.99	<0.01	
			High	0.97 (0.97-0.98)	27 (25-28)	>0.99	<0.01	
Tight lockdown with face masks	Low (LT1)	Low	Low	0.21 (0.21-0.22)	124 (115-137)	0.80 (0.79-0.80)	0.24	
			High	0.26 (0.26-0.27)	112 (102-122)	0.85 (0.85-0.86)	0.22	
		High	Low	0.22 (0.22-0.23)	121 (113-134)	0.81 (0.80-0.81)	0.16	
			High	0.27 (0.27-0.28)	107 (100-119)	0.86 (0.86-0.86)	0.27	
	High (HT2)	Low	Low	0.88 (0.88-0.89)	37 (36-39)	>0.99	<0.01	
			High	0.89 (0.89-0.90)	36 (35-38)	>0.99	<0.01	
		High	Low	0.89 (0.88-0.89)	37 (35-39)	>0.99	<0.01	
			High	0.90 (0.89-0.90)	36 (34-38)	>0.99	<0.01	
	High (HT1)	Low	Low	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	
			High	0.97 (0.97-0.97)	26 (26-28)	>0.99	<0.01	
		High	Low	0.97 (0.97-0.97)	27 (26-29)	>0.99	<0.01	
			High	0.97 (0.97-0.97)	27 (26-28)	>0.99	<0.01	

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Table S9

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epidemics averted	Peak population in isolation
Face masks with 16 sectors imposed when 1% of population is symptomatic	Low (LT1)	Low	Low	0.10 (0.095-0.10)	121 (110-136)	0.56 (0.55-0.58)	0.24	
			High	0.19 (0.18-0.20)	97 (90-105)	0.78 (0.77-0.78)	0.14	
		High	Low	0.11 (0.10-0.11)	118 (109-128)	0.58 (0.57-0.59)	0.23	
			High	0.21 (0.21-0.22)	94 (87-104)	0.78 (0.77-0.79)	0.14	
	High (HT2)	Low	Low	0.74 (0.74-0.75)	40 (38-42)	>0.99	<0.01	
			High	0.78 (0.77-0.79)	38 (37-40)	>0.99	<0.01	
		High	Low	0.74 (0.74-0.75)	40 (38-42)	>0.99	<0.01	
			High	0.78 (0.78-0.79)	38 (36-40)	>0.99	<0.01	
	High (HT1)	Low	Low	0.92 (0.92-0.93)	29 (28-30)	>0.99	<0.01	
			High	0.94 (0.94-0.94)	28 (27-29)	>0.99	<0.01	
		High	Low	0.92 (0.92-0.93)	29 (28-30)	>0.99	<0.01	
			High	0.94 (0.94-0.94)	28 (27-29)	>0.99	<0.01	
Face masks with 16 sectors imposed when 0.1% of population is symptomatic	Low (LT1)	Low	Low	0.051 (0.045-0.058)	163 (138-192)	0.52 (0.47-0.52)	0.18	
			High	0.13 (0.12-0.14)	116 (104-128)	0.77 (0.76-0.78)	0.16	
		High	Low	0.068 (0.062-0.076)	146 (132-163)	0.55 (0.53-0.56)	0.22	
			High	0.17 (0.16-0.18)	101 (95-112)	0.78 (0.77-0.78)	0.18	
	High (HT2)	Low	Low	0.63 (0.61-0.66)	44 (42-46)	>0.99	<0.01	
			High	0.69 (0.67-0.71)	42 (40-43)	>0.99	<0.01	
		High	Low	0.64 (0.62-0.67)	44 (42-45)	>0.99	<0.01	
			High	0.71 (0.69-0.73)	41 (40-43)	>0.99	<0.01	
	High (HT1)	Low	Low	0.87 (0.86-0.88)	31 (30-33)	>0.99	<0.01	
			High	0.90 (0.89-0.90)	30 (29-31)	>0.99	<0.01	
		High	Low	0.88 (0.87-0.88)	31 (30-32)	>0.99	<0.01	
			High	0.90 (0.90-0.91)	30 (29-31)	>0.99	<0.01	

Table S10

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epid'ics averted	Peak population in isolation
Face masks with remove-and-isolate on ~day 2 starting when 1% of population is symptomatic	Low (LT1)	Low	Low	0.059 (0.056-0.064)	89 (82-104)	0.17 (0.16-0.19)	0.24	0.091 (0.086-0.097)
			High	0.086 (0.082-0.093)	76 (69-88)	0.30 (0.28-0.31)	0.10	0.13 (0.13-0.14)
		High	Low	0.061(0.057-0.066)	87 (77-97)	0.17 (0.16-0.19)	0.26	0.093 (0.087-0.10)
			High	0.097 (0.091-0.10)	74 (68-83)	0.34 (0.31-0.35)	0.18	0.15 (0.14-0.16)
	High (HT2)	Low	Low	0.81 (0.81-0.82)	38 (37-40)	>0.99	<0.01	0.85 (0.85-0.86)
			High	0.84 (0.83-0.84)	37 (36-39)	>0.99	<0.01	0.87 (0.87-0.87)
		High	Low	0.81 (0.81-0.82)	38 (36-40)	>0.99	<0.01	0.85 (0.85-0.86)
			High	0.84 (0.83-0.84)	37 (35-39)	>0.99	<0.01	0.87 (0.87-0.87)
	High (HT1)	Low	Low	0.96 (0.96-0.96)	28 (26-29)	>0.99	<0.01	0.94 (0.94-0.95)
			High	0.96 (0.96-0.97)	27 (26-28)	>0.99	<0.01	0.95 (0.95-0.95)
		High	Low	0.96 (0.96-0.96)	28 (27-29)	>0.99	<0.01	0.94 (0.94-0.95)
			High	0.97 (0.96-0.97)	27 (26-28)	>0.99	<0.01	0.95 (0.95-0.95)
Face masks with remove-and-isolate on ~day 2 starting when 0.1% of population symptomatic	Low (LT1)	Low	Low	0.007 (0.006-0.009)	59 (49-81)	0.020 (0.015-0.026)	0.24	0.011 (0.009-0.014)
			High	0.013 (0.010-0.017)	66 (52-83)	0.058 (0.038-0.11)	0.18	0.021 (0.016-0.027)
		High	Low	0.007 (0.006-0.009)	58 (50-69)	0.020 (0.015-0.027)	0.21	0.011 (0.009-0.014)
			High	0.016 (0.013-0.021)	72 (58-102)	0.097 (0.061-0.14)	0.14	0.026 (0.021-0.033)
	High (HT2)	Low	Low	0.78 (0.78-0.79)	40 (39-42)	>0.99	<0.01	0.83 (0.82-0.83)
			High	0.80 (0.80-0.81)	39 (37-40)	>0.99	<0.01	0.84 (0.84-0.85)
		High	Low	0.78 (0.78-0.79)	40 (39-42)	>0.99	<0.01	0.83 (0.82-0.83)
			High	0.81 (0.80-0.81)	38 (37-40)	>0.99	<0.01	0.85 (0.84-0.85)
	High (HT1)	Low	Low	0.95 (0.95-0.95)	28 (27-30)	>0.99	<0.01	0.94 (0.94-0.94)
			High	0.96 (0.96-0.96)	28 (26-29)	>0.99	<0.01	0.94 (0.94-0.95)
		High	Low	0.95 (0.95-0.95)	28 (27-29)	>0.99	<0.01	0.94 (0.94-0.94)
			High	0.96 (0.96-0.96)	28 (27-29)	>0.99	<0.01	0.94 (0.94-0.95)

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Table S11

Interventions	Transmission	Movement	Interaction	Peak proportion infected	Time to peak infection	Total proportion infected	Epid'ics averted	Peak population in isolation
Face masks, sectoring, remove-and-isolate	Low (LT1)	Low	Low	0.001 (0.001-0.001)	24 (22-27)	0.002 (0.002-0.002)	0.93	0.002 (0.002-0.002)
			High	0.002 (0.001-0.002)	32 (19-49)	0.003 (0.002-0.04)	0.87	0.002 (0.002-0.003)
		High	Low	0.001 (0.001-0.002)	22 (20-23)	0.001 (0.001-0.003)	0.94	0.002 (0.001-0.002)
			High	0.002 (0.001-0.003)	30 (24-40)	0.003 (0.002-0.008)	0.86	0.003 (0.002-0.004)
	High (HT2)	Low	Low	0.090 (0.075-0.11)	132 (99-192)	0.80 (0.62-0.90)	0.23	0.11 (0.091-0.13)
			High	0.18 (0.16-0.21)	98 (83-115)	0.94 (0.94-0.95)	0.22	0.22 (0.20-0.25)
		High	Low	0.14 (0.13-0.16)	121 (107-146)	0.90 (0.89-0.91)	0.18	0.17 (0.15-0.19)
			High	0.25 (0.23-0.27)	78 (70-90)	0.94 (0.94-0.95)	0.21	0.30 (0.27-0.32)
	High (HT1)	Low	Low	0.25 (0.23-0.29)	79 (69-96)	>0.99	0.08	0.29 (0.26-0.33)
			High	0.33 (0.31-0.37)	62 (53-70)	>0.99	0.04	0.38 (0.36-0.42)
		High	Low	0.32 (0.30-0.36)	68 (57-78)	>0.99	0.07	0.37 (0.33-0.40)
			High	0.44 (0.41-0.50)	48 (45-55)	>0.99	<0.01	0.50 (0.47-0.56)
Face masks, sectoring, lockdown	Low (LT1)	Low	Low	0.020 (0.008-0.026)	234 (156-311)	0.32 (0.091-0.40)	0.52	
			High	0.060 (0.053-0.065)	242 (194-294)	0.75 (0.74-0.76)	0.26	
		High	Low	0.031 (0.026-0.036)	269 (184-351)	0.46 (0.42-0.50)	0.46	
			High	0.082 (0.076-0.090)	182 (150-212)	0.78 (0.77-0.78)	0.26	
	High (HT2)	Low	Low	0.19 (0.16-0.21)	113 (94-133)	>0.99	<0.01	
			High	0.24 (0.22-0.27)	91 (76-104)	>0.99	<0.01	
		High	Low	0.22 (0.20-0.25)	99 (85-117)	>0.99	<0.01	
			High	0.29 (0.27-0.32)	76 (67-85)	>0.99	<0.01	
	High (HT1)	Low	Low	0.27 (0.24-0.30)	77 (66-90)	>0.99	<0.01	
			High	0.33 (0.31-0.37)	62 (53-70)	>0.99	<0.01	
		High	Low	0.33 (0.30-0.37)	65 (58-77)	>0.99	<0.01	
			High	0.40 (0.37-0.45)	55 (48-62)	>0.99	<0.01	
Face masks, remove-and-isolate, lockdown	Low (LT1)	Low	Low	0.002 (0.001-0.002)	32 (26-43)	0.003 (0.002-0.004)	0.80	0.003 (0.002-0.003)
			High	0.002 (0.001-0.003)	31 (25-50)	0.004 (0.002-0.007)	0.73	0.003 (0.002-0.005)
		High	Low	0.002 (0.001-0.002)	32 (24-38)	0.003 (0.002-0.005)	0.85	0.003 (0.002-0.004)
			High	0.002 (0.001-0.004)	29 (23-52)	0.004 (0.002-0.011)	0.70	0.003 (0.002-0.006)
	High (HT2)	Low	Low	0.78 (0.77-0.78)	44 (42-46)	>0.99	0.10	0.82 (0.82-0.83)
			High	0.80 (0.80-0.81)	42 (40-44)	>0.99	0.10	0.84 (0.84-0.84)
		High	Low	0.78 (0.77-0.79)	44 (42-46)	>0.99	0.10	0.82 (0.82-0.83)
			High	0.81 (0.80-0.81)	42 (40-45)	>0.99	0.08	0.84 (0.84-0.85)
	High (HT1)	Low	Low	0.95 (0.95-0.95)	30 (28-31)	>0.99	0.04	0.94 (0.93-0.94)
			High	0.96 (0.95-0.96)	29 (28-30)	>0.99	0.02	0.94 (0.94-0.94)
		High	Low	0.95 (0.95-0.96)	29 (38-31)	>0.99	<0.01	0.94 (0.93-0.94)
			High	0.96 (0.96-0.96)	28 (27-30)	>0.99	0.02	0.94 (0.94-0.94)
Face masks, sectoring, remove-and-isolate, lockdown	Low (LT1)	Low	Low	0.001 (0.001-0.002)	23 (19-28)	0.002 (0.002-0.003)	0.92	0.002 (0.002-0.002)
			High	0.002 (0.001-0.002)	28 (20-43)	0.003 (0.002-0.005)	0.88	0.002 (0.002-0.003)
		High	Low	0.002 (0.001-0.002)	26 (21-32)	0.002 (0.002-0.004)	0.94	0.002 (0.002-0.003)
			High	0.002 (0.001-0.002)	30 (25-43)	0.003 (0.002-0.006)	0.84	0.002 (0.002-0.004)
	High (HT2)	Low	Low	0.035 (0.027-0.050)	74 (51-115)	0.16 (0.060-0.29)	0.24	0.041 (0.032-0.060)
			High	0.14 (0.12-0.15)	129 (106-160)	0.94 (0.93-0.95)	0.16	0.16 (0.14-0.18)
		High	Low	0.068 (0.046-0.088)	121 (79-158)	0.53 (0.28-0.73)	0.28	0.083 (0.053-0.11)
			High	0.18 (0.16-0.20)	106 (89-124)	0.95 (0.95-0.95)	0.16	0.21 (0.19-0.24)
	High (HT1)	Low	Low	0.17 (0.14-0.21)	97 (75-124)	>0.99	0.07	0.19 (0.15-0.23)
			High	0.27 (0.24-0.30)	77 (65-86)	>0.99	0.04	0.30 (0.28-0.34)
		High	Low	0.24 (0.21-0.27)	84 (73-98)	>0.99	0.08	0.27 (0.24-0.30)
			High	0.34 (0.31-0.38)	63 (55-71)	>0.99	0.06	0.38 (0.35-0.42)

In table S11, the camp is divided into 16 sectors (n = 16), remove-and-isolate occurs on average on day 2 (b = 2), and lockdown is moderate (r_l = 0.01, v_l = 0.1).

Table S12

Movement	Interaction	Low transmission 1	Low transmission 2	High Transmission 1	High Transmission 2
Low	Low	4.02 (6.02) 1, 2, 4, 6, 8	4.32 (6.67) 1, 2, 4, 6, 9	22.05 (68.70) 10, 16, 21, 27, 37	14.48 (34.41) 6, 10, 14, 18, 25
	High	4.64 (7.83) 1, 3, 4, 6, 10	4.47 (6.89) 1, 3, 4, 6, 9	23.83 (88.17) 11, 17, 22, 30, 41	15.26 (38.97) 6, 11, 15, 19, 27
High	Low	4.05 (6.40) 1, 2, 4, 6, 9	4.34 (6.72) 1, 2, 4, 6, 9	22.06 (70.63) 10, 16, 21, 27, 38	14.44 (35.28) 6, 10, 14, 18, 25
	High	4.63 (8.10) 1, 3, 4, 6, 10	4.51 (7.22) 1, 3, 4, 6, 9	23.79 (91.10) 11, 17, 22, 30, 42	15.38 (42.20) 6, 11, 15, 19, 27

Table S12 reports the basic reproduction number R_0 for COVID-19 in the model population for each scenario combination (*i.e.*, transmission rate, movement, and interaction rate) in the absence of intervention. In each cell, the first line reports R_0 and (in parentheses) the variance of the number of individuals infected by the index case. The second line reports the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles for the number of people infected by the index case.

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