

BMJ Open Evaluating the contributions of strategies to prevent SARS-CoV-2 transmission in the healthcare setting: a modelling study

Xueting Qiu ¹, Joel C Miller,² Derek R MacFadden,³ William P Hanage¹

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¹Department of Epidemiology, Harvard University T H Chan School of Public Health, Boston, Massachusetts, USA

²School of Engineering at Mathematical Sciences, La Trobe University - Bundoora Campus, Melbourne, Victoria, Australia

³Clinical Epidemiology Program, Ottawa Hospital Research Institute, Ottawa, Ontario, Canada

Correspondence to

William P Hanage;
whanage@hsph.harvard.edu

ABSTRACT

Introduction Since its onset, the COVID-19 pandemic has caused significant morbidity and mortality worldwide, with particularly severe outcomes in healthcare institutions and congregate settings. To mitigate spread, healthcare systems have been cohorting patients to limit contacts between uninfected patients and potentially infected patients or healthcare workers (HCWs). A major challenge in managing the pandemic is the presence of currently asymptomatic/presymptomatic individuals capable of transmitting the virus, who could introduce COVID-19 into uninfected cohorts. The optimal combination of personal protective equipment (PPE), testing and other approaches to prevent these events is unclear, especially in light of ongoing limited resources.

Methods Using stochastic simulations with a susceptible-exposed-infected-recovered dynamic model, we quantified and compared the impacts of PPE use, patient and HCWs surveillance testing and subcohorting strategies.

Results In the base case without testing or PPE, the healthcare system was rapidly overwhelmed, and became a net contributor to the force of infection. We found that effective use of PPE by both HCWs and patients could prevent this scenario, while random testing of apparently asymptomatic/presymptomatic individuals on a weekly basis was less effective. We also found that even imperfect use of PPE could provide substantial protection by decreasing the force of infection. Importantly, we found that creating smaller patient/HCW-interaction subcohorts can provide additional resilience to outbreak development with limited resources.

Conclusion These findings reinforce the importance of ensuring adequate PPE supplies even in the absence of testing and provide support for strict subcohorting regimens to reduce outbreak potential in healthcare institutions.

INTRODUCTION

The COVID-19 pandemic is one of the most serious threats to public health in over a century. Early reports indicated a relatively large proportion of cases among healthcare workers (HCWs).^{1–3} Not only is this a major concern for the health of frontline responders, there is also a risk of transmission to patients. For this reason, the design and

Strengths and limitations of this study

- This study focuses on the important high-risk populations of non-COVID patients and healthcare workers in the healthcare settings, including long-term care facilities and nursing homes.
- The model proposes optimal and most effective measures to protect individuals in healthcare settings even with scarce resources.
- The model is deliberately general and does not include other potentially important factors (such as non-pharmaceutical interventions) influencing the course of the pandemic.
- We do not include any overdispersed transmission (super-spreading events) in the model.
- Though not modelled explicitly, overdispersion would be expected to increase the impact of the subcohorting strategy by limiting the total potential outbreak cluster size.

implementation of cohorting strategies to restrict contact between COVID-19 patients and the rest of the healthcare system are of great importance. For example, in some locations, hospitals or other facilities are being exclusively dedicated for COVID-19 patients, separate from others reserved for the non-COVID cohort and alternate care facilities are in the process of being established.^{4 5}

As the pandemic progresses, the use of personal protective equipment (PPE), together with regular testing to identify infected individuals, are important ways of preventing transmission. The large existence of transmissions from asymptomatic or presymptomatic individuals presents a sobering challenge to infection control.⁶ Thus, testing to detect these invisibly infected individuals seems to be the key for prevention. This is particularly important in healthcare systems throughout the continuum of care, including hospitals, primary care and long-term care facilities such as nursing homes, which have been a focus of the early

pandemic. Once SARS-CoV-2 is introduced to these settings, rapid transmission has been observed.⁷ But testing is not perfect, unless we stop all physical HCW–patient interactions, it is not possible to keep the disease out of healthcare settings.

To provide safe interactions during the healthcare process, besides regular testing, the effective use of PPE is the major proposed measure to prevent the spread of infection to and from patients and HCWs, but the shortage of PPE has already proven a critical problem in many healthcare institutions⁸ and there is no reason to think this will change in the event of future waves of the pandemic. It is often suggested that cohorting low-risk patients is a way to preserve scarce PPE, but for this to be effective and safe, again it requires an extremely high accuracy of rapid virological testing to detect new infections and prevent further transmissions. Such testing regimens are not currently implemented in many settings in the USA⁸ or worldwide. With the reality of supply shortage and the high risks of infection in these healthcare settings, the optimal combination of viral testing, PPE and other non-pharmaceutical prevention measures has not been quantified.

Determining optimal interventions during epidemics can be challenging, as there is often limited time and resources for launching large prospective studies. Moreover, informed decisions about infection control practices need to be made early on. Dynamic models offer a scientific framework with which to predict epidemic outcomes using established parameters and known disease transmission characteristics. Such models have been employed to evaluate potential COVID-19 management approaches,⁹ that have informed physical distancing policy throughout the world. Therefore, we can use these models to help us better plan PPE use, diagnostic testing and other prevention measures.

Using a modified stochastic susceptible-exposed-infected-recovered (SEIR) model, we seek to evaluate the impacts of PPE, diagnostic testing and HCWs/patients cohorting strategies in the context of the interaction between HCWs and non-COVID patients. In detail, PPE use refers to wearing face masks as it is the most practical way to implement in healthcare settings; diagnostic testing indicates weekly surveillance testing and cohorting is a measure to separate a population into different groups based on infection status to limit the interactions between groups and thus reduce transmissions.¹⁰ Since we focus on non-COVID cohorts, we customise a subcohorting strategy using different group sizes to manage the HCWs and patients' interaction to contain introductions. We found that although regular testing can identify asymptomatic/presymptomatic individuals and reduce the force of infection (FOI), PPE is the most effective component to prevent COVID-19 transmission in healthcare settings. Importantly, our modelling results emphasised the role of subcohorting strategy where the population is divided into subgroups, to reduce the probability of large outbreaks; that is, dividing the non-COVID patients

and HCWs into multiple subcohorts with smaller sizes can contain the impact of an introduction to a smaller outbreak when other interventions are not available.

METHODS

We use a basic transmission model. It has two major components: transmission in the general population to factor in the outbreak situation in the general public outside the healthcare system, and transmission within a cohort of HCWs and patients who are initially not infected with SARS-CoV-2, that is, the non-COVID cohort. Individuals in the model begin as susceptible (S). Following a transmission event, they move into the exposed class (E). After that they become infectious (I). A fraction of these remains asymptomatic (I_A) and so can only be identified through testing. Another fraction of infections is initially 'presymptomatic' (I_1) and eventually exhibit symptoms (I_2) which could lead to identification. Finally, they recover with immunity (R). We note that we are modelling the risk of transmission and the most effective ways to minimise it in healthcare settings, which may not be the direct effects of mitigation strategies.

The non-COVID HCWs and patient cohort is modelled stochastically using a Gillespie-Doob algorithm.¹¹ The cohort experiences introductions either through HCWs infected in the broader community or patients (which may come from visitors or from newly admitted patients who are incorrectly identified as uninfected). Within the non-COVID cohort, we assume that once individuals become symptomatic, they are identified and removed. We use stochastic simulations to track these components. To demonstrate the impacts of control measures and cohort size, we focus on a single cohort of HCWs and the patients. The specific details of our simulations are described in the online supplemental appendix. The simulations are scripted in Python (available at <https://github.com/joelmiller/HospitalCOVID19>).

Variables and parameters

We will use the variables S , E , I_A , I_1 , I_2 and R for two purposes: both to denote the number of individuals in a particular state, and also as a shorthand to refer to the status of an individual. So the number of S individuals in the population is S , the number of E HCWs in the cohort is E_H and the number of asymptotically infected patients is $I_{A,P}$.

Table 1 shows the variables we track with the models, and tables 2 and 3 show the parameters and their default values.

The basic reproduction number in the general population is

$$R_0 = (1 - q) \left(\frac{\lambda_1}{\gamma_{I,1}} + \frac{\lambda_2}{\gamma_{I,2}} \right) + q \frac{\lambda_A}{\gamma_A}$$

With our default values of λ and γ from table 2, we find $R_0 = 2.5 - 0.25q$. If all individuals become symptomatic ($q=0$), then $R_0 = 2.5$, while if all become asymptomatic ($q=1$), then $R_0 = 2.25$. The R_0 value is in the range of estimates from

Table 1 The variables used in the model

Variable	Definition
S, E, I_A, I_1, I_2, R	Number of susceptible, exposed, asymptomatic infectious, presymptomatic infectious, symptomatic infectious and recovered individuals in the general population.
$S_P, E_P, I_{A,P}, I_{1,P}, R_P$	Number of patients in the cohort. We assume that symptomatic cases are removed immediately.
$S_H, E_H, I_{A,H}, I_{1,H}, Q_H, R_H$	Number of HCWs of each status. We assume that identified infections are moved into a quarantine class Q_H until recovering.
$N_P = S_P + E_P + I_{A,P} + I_{1,P} + R_P$ and $N_H = S_H + E_H + I_{A,H} + I_{1,H} + R_H$	Number of patients and healthcare workers active in the cohort (no symptomatic or quarantined individuals).*

*The $I_{2,P}$ $I_{2,H}$ classes are neglected in the model because we assume individuals are removed as soon as they become symptomatic.

previous studies.^{12–14} We assume that the average transmission rate in asymptomatic infection is the same as that in presymptomatic infection, that is, $\lambda_A = \lambda_1$.

Within the healthcare setting, we expect that HCWs are at high risk of infection, which may be reduced but not eliminated by PPE. This is because of the frequent close interactions between HCWs and their patients. Additionally, this expectation is supported by the observed high

Table 2 Default parameter values of disease spread in general population

Parameter	Default value	Definition
λ_1	1/4	Average transmission rate from presymptomatic I_1 individuals.
λ_2	2/7	Average transmission rate from symptomatic I_2 individuals.
λ_A	λ_1	Average transmission rate from asymptomatic I_A individuals.
λ	$\lambda_1 I_1 + \lambda_2 I_2 + \lambda_A I_A$	Overall transmission rate (force of infection) to S individuals in general public.
γ_E	1/3	Rate of a transition out of E to either I_1 or I_A .
q	1/2	The probability a transition from E is to I_A .
$\gamma_{1,1}$	1/2	Rate of an $I_1 \rightarrow I_2$ transition.
$\gamma_{1,2}$	1/7	Rate of an $I_2 \rightarrow R$ transition.
γ_A	1/9	The rate of an $I_A \rightarrow R$ transition.

Table 3 The default values for healthcare-related parameters

Parameter	Default value	Definition
γ_Q	1/14	The rate at which quarantined individuals are released.
ω	0	Weekly testing rate of HCWs and patients.
ρ	0	Probability a non-symptomatic individual would get admitted.
C_H	0.1	The relative transmission from the general public to HCWs.
C_P	0.1	The relative transmission from the general public to patients (it captures risk from visitors).
C_{PP}	0.5	Scaling factor for patient-to-patient transmission relative to number expected an infected individual would cause in general population.
C_{PH}	2	Scaling factor for patient to HCW transmission, representing that an infected patient transmits to HCWs at a rate that is C_{PH} times that of a general member of the public to other members of the public.
C_{HP}	2	Scaling factor for HCW to patient transmission, representing that an infected HCWs transmits to patients at a rate that is C_{HP} times that of a general member of the public to other members of the public.
C_{HH}	1	Scaling factor for HCW–HCW transmission within the cohort, representing that an infected HCWs transmits to HCWs at a rate that is C_{HH} times that of a general member of the public to other members of the public.
\hat{N}	1000	The typical size of a cohort in the absence of transmission. The natural discharge rate is b/\hat{N} . In the absence of disease N_P would oscillate around \hat{N} .
$\hat{N}/4$	250	The total number of HCWs allocated to the cohort (changes when HCWs go into or return from quarantine).
b	$\hat{N}/14$	Natural rate at which new patients arrive at a cohort.

HCW, healthcare workers.

rates of infection among HCWs in many different populations.^{13 15 16} This is reflected in the large value of C_{PH} representing that an infected patient transmits to HCWs at a rate that is C_{PH} times that of a general member of the public. We refer to C_{PH} and following similar parameters as ‘scaling factors’ to capture the relative transmission rate between different populations. We anticipate that in the absence of intervention, the transmission rate from HCWs to patients will also be relatively high. HCWs transmit to patients at a rate that is C_{HP} times that of

a general member of the public to other members of the public. It should be noted that patients typically outnumber HCWs. So the transmissions from patients to HCWs are concentrated in a smaller population and HCWs experience potential repeated exposures from different patients. This means that all else being equal, the FOI experienced by HCWs is higher than that of patients. So even if $C_{PH} = C_{HP}$, this represents a higher transmission probability per interaction from patients to HCWs than vice versa.

Parameter values for different scenarios

To quantify the impacts of different interventions, we defined parameter values for different scenarios in addition to the base model with the default parameter values without interventions above.

In detail, in the scenarios with viral testing, we set the testing rate of patients and HCWs to be weekly that is, $\omega = 1/7$, where general population has no surveillance viral testing.

- ▶ To explore the impacts of PPE, several scenarios have been defined:
 - At best, PPE reduces the scaling factor to 1/8 of the default, that is, $C_{PP} = 0.0625$, $C_{PH} = 0.25$, $C_{HP} = 0.25$ and $C_{HH} = 0.125$.
 - When only HCWs use PPE, we set $C_{PP} = 0.5$ (the default for between patient transmissions), $C_{PH} = 0.25$, $C_{HP} = 0.25$ and $C_{HH} = 0.125$.
 - When both HCWs and patients use PPE, we set $C_{PP} = 0.0625$, $C_{PH} = 0.25$, $C_{HP} = 0.25$ and $C_{HH} = 0.125$.
 - The 75% effective PPE is defined as reducing the scaling factor to 1/4 of the default transmissions, that is, $C_{PP} = 0.125$, $C_{PH} = 0.5$, $C_{HP} = 0.5$ and $C_{HH} = 0.25$.
 - The 50% effective PPE is defined as reducing the scaling factor to half of the default transmissions, that is, $C_{PP} = 0.25$, $C_{PH} = 1$, $C_{HP} = 1$ and $C_{HH} = 0.5$.
- ▶ To account for the uncertainty of the proportion and the duration of asymptomatic infections, we set
 - Lower proportion of asymptomatic infections: $q = 0.3$.
 - Higher proportion of asymptomatic infections: $q = 0.7$.
 - Shorter duration of asymptomatic infections: $\gamma_A = 1/5$.
- ▶ To explore the impacts of subcohort size in the non-COVID patient/HCWs cohort, we run simulations with patient cohort size as 50, 100, 200, 400, 800 and 1600, respectively, with the probability a non-symptomatic individual would get admitted as $\rho = 0.05$. And the corresponding number of HCWs in each cohort is 12, 25, 50, 100, 200 and 400, respectively, to maintain a patient:HCW ratio as 4.

Patient and public involvement

Patients or the public were not involved in the design, or conduct, or reporting or dissemination plans of our research. This study takes a pure mathematical modelling approach to examine the impact of different strategies, based on parameter estimates drawn from the literature.

RESULTS

Base model without testing and PPE

We find that in the absence of any interventions to prevent introduction of SARS-CoV-2 to the non-COVID cohort, HCWs rapidly become infected (figure 1A), consistent with general observations from the early stages of the current pandemic.¹¹⁷ While this leads to a high FOI to patients in the early stage of the epidemic (figure 1A), later, once many of the HCWs have developed immunity or become symptomatic and moved into quarantine, the FOI to patients drops. At later stages, as the epidemic grows in the general population, the patients are at reduced risk. This is because the patients primarily interact with HCWs who have been immunised by infection, meanwhile they have relatively little interaction with other patients or the general public.

Impacts of regular testing

Accurate virological testing is important to implement containment measures where a case is identified. HCWs have been recognised as an important group to receive testing both because of the exposure risks inherent in their profession and the potential consequences of their infection for others.⁴ Testing, especially while it has been scarce, has been understandably directed at those with symptoms. However, COVID-19 has a range of presentations, and infectious individuals may be asymptomatic or presymptomatic.¹⁸ In the absence of testing, the asymptomatic or presymptomatic patients and HCWs cannot be removed from the population and pose an infection risk to the rest of the cohort. We model this as a random testing rate of the non-COVID patients and HCWs cohort (note they may have been infected but only demonstrating asymptomatic or presymptomatic) on a weekly basis $\omega = 1/7$, we see a significantly lower FOI on both HCWs and patients (figure 1B). It takes longer for the HCWs to all become infected, and the peak level of HCWs quarantine is higher as a result of more cases being identified. These impacts are expected to be larger for higher testing rates.

Impacts of PPE

PPE, representing facial masking in this simulation for practical implementation, substantially delays the peak of infection and reduces FOI, even when only used by HCWs (figure 1C–E). In many locations, PPE supply has been limited, leading to reuse of normally disposable facial masking items or in some cases improvised equipment. Our model also considers the potential flaws of PPE use throughout the non-COVID patients/HCWs cohort. So we investigated the impact of less effective PPE (whether due to improper use or lower quality equipment). we define perfect PPE as reducing the transmission to 1/8 of default values; imperfect PPE is defined by the reduced effectiveness of PPE in preventing transmission, and can be considered to represent situations in which PPE shortages lead to diversion of supply to the COVID-19 cohort. For example, 50% effective PPE means that the use of PPE reduces the transmission rate by half. Based on the simulations (figure 2), we find that even half effective PPE (figure 2B) can bring down the FOI of HCWs near to that in the general population.

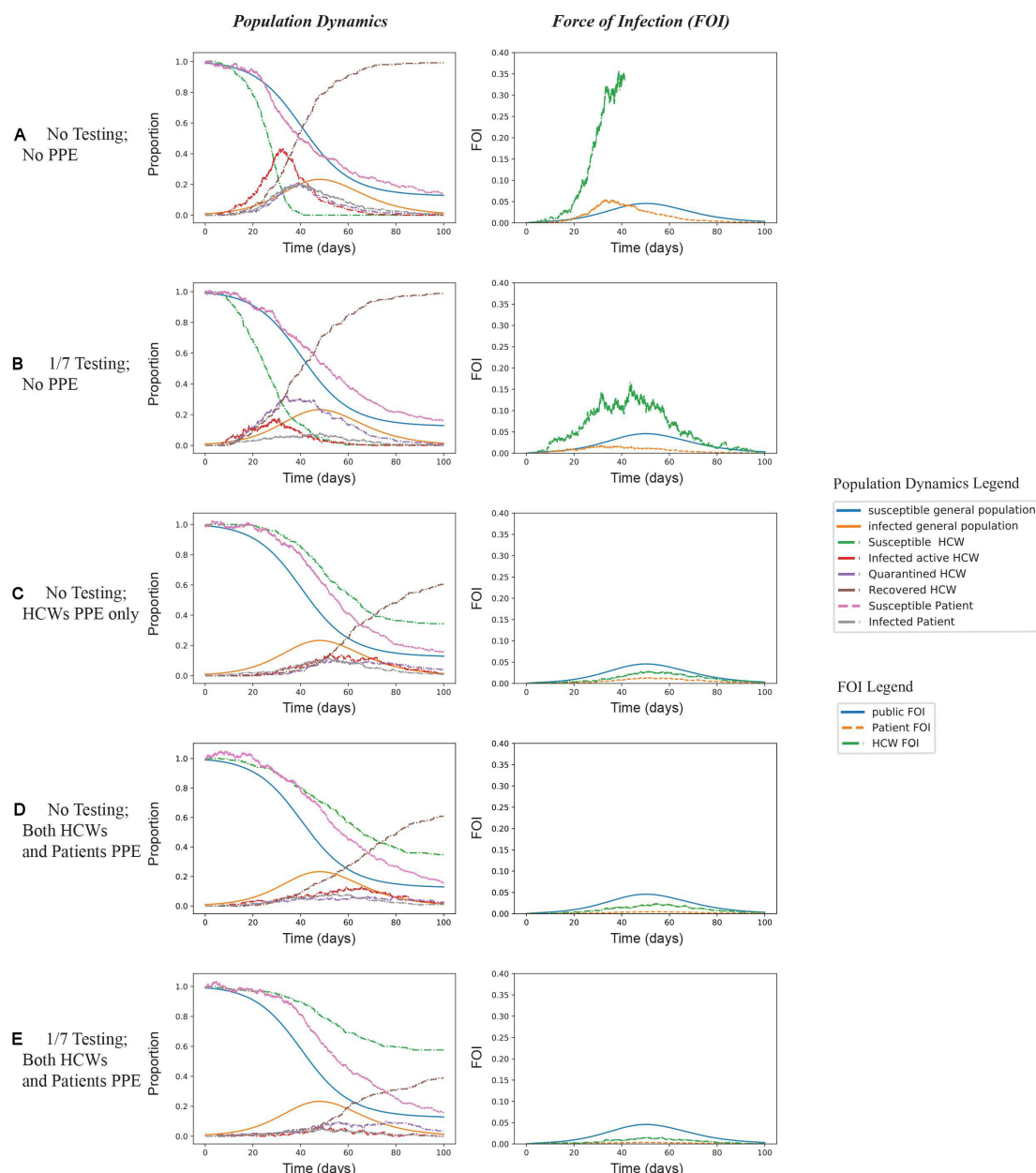


Figure 1 Comparing different scenarios of testing and PPE. Plots show the susceptible and infected portions of the cohort, and the force of infection (FOI). When there is no testing and no PPE (A), all HCWs are rapidly infected. The calculation of FOI on HCWs terminates once all have been infected. At peak about 40% of the HCWs are infected (not in quarantine), and shortly thereafter about 20% of the HCWs are under quarantine. The plots show that both testing (B) and PPE (C and D) can reduce the FOI. But PPE has more substantial impacts on delaying and reducing the HCWs infection peak and the FOI. Noticeably, even only HCWs use PPE in (C), the infection peak and FOI in both HCWs and patients are reduced. (E) The impact of simultaneous use of testing and effective PPE. HCW, health care workers; PPE, personal protective equipment.

Impacts of asymptomatic infection

The estimated proportion of asymptomatic infections (18%–75%) varies among currently available epidemiological studies,^{7 19–22} reflecting the difficulty of accurately assessing this parameter.²³ An advantage of mathematical simulations is that we can examine the consequences for scenarios in which varying proportions of infections were asymptomatic (q), in the presence of testing to detect them at rate $\omega=1/7$ (figure 3). As shown, as the proportion of asymptomatic infections increases, the FOI among

HCWs increases with it, leading it to peak earlier with concomitant effects on patients (figure 3A–C).

The effect of this is minor in comparison with the consequences of reducing the duration of the asymptomatic period (figure 3D), which intuitively reduces the opportunity for exposure and transmission. This suggests the importance of testing for detecting asymptomatic or presymptomatic-infected individuals among both HCWs and patients promptly. It also indicates the importance of PPE use among as many individuals as possible, in order

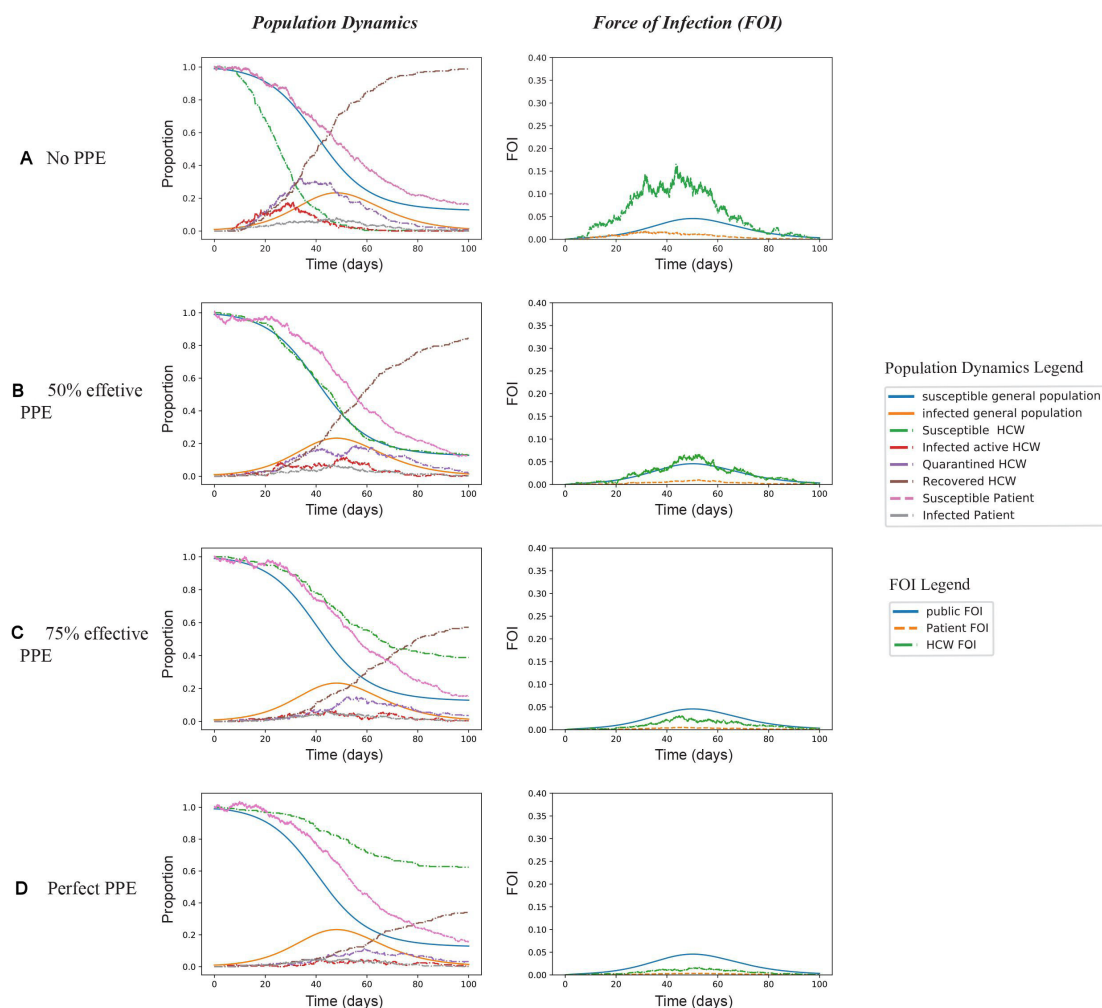


Figure 2 The relative protection of PPE in a non-COVID-19 cohort. In all scenarios, testing rate $\omega=1/7$ but with PPE of varying efficacy. At best, we assume PPE reduces the nosocomial transmission to $1/8$ of the default values (D); Plot (A) represents no PPE use; (B) represents prevention of 50% of transmission events; (C) represents prevention of 75% of transmission events. Results indicate that even modest reductions in transmission can reduce the force of infection inside healthcare setting. HCW, healthcare workers; PPE, personal protective equipment

to limit unwitting transmission from individuals not yet tested or impossible to be tested due to limited supply.

Impacts of subcohort size

The probability that a given introduction establishes in a cohort is independent of the cohort size L once L is reasonably large. However, the expected number of introductions is proportional to L . For this reason, the probability a cohort does not have a successful introduction increases as L decreases.

Assuming the introduction rate is proportional to the cohort size, the probability infection establishes itself into a cohort of size L is e^{-kL} for some $k>0$, where e is Euler's number (the base of the natural logarithm) and k is the successful introduction rate per individual. The value of k increases with the rate at which non-symptomatic-infected individuals are admitted, the rate at which the general public transmits to patients or HCWs and the transmission rate between individuals in the healthcare system. The value of k decreases as the recovery rates and testing

rates increase. The probability of at least one successful introduction into a cohort is thus $1 - e^{-kL}$.

If infection is established within a cohort, it will typically infect some fraction of the total population. Like typical epidemics, this fraction is independent of the population size. So for larger populations, the number of infections increases.

This motivates the following observation: given a collection of cohorts that are small enough to each have a non-negligible chance of escaping infection, then joining them together increases the risk to all members of the cohorts. The cumulative distribution function of outbreak sizes for cohorts of different sizes is shown in figure 4. This suggests that dividing the cohort into smaller subcohorts and thus minimising the risk of successful introduction can be an effective way to reduce the risk of infection within the cohorts. Smaller cohorts also reduce the amount of additional testing required to identify secondary transmission among contacts once one case is identified.

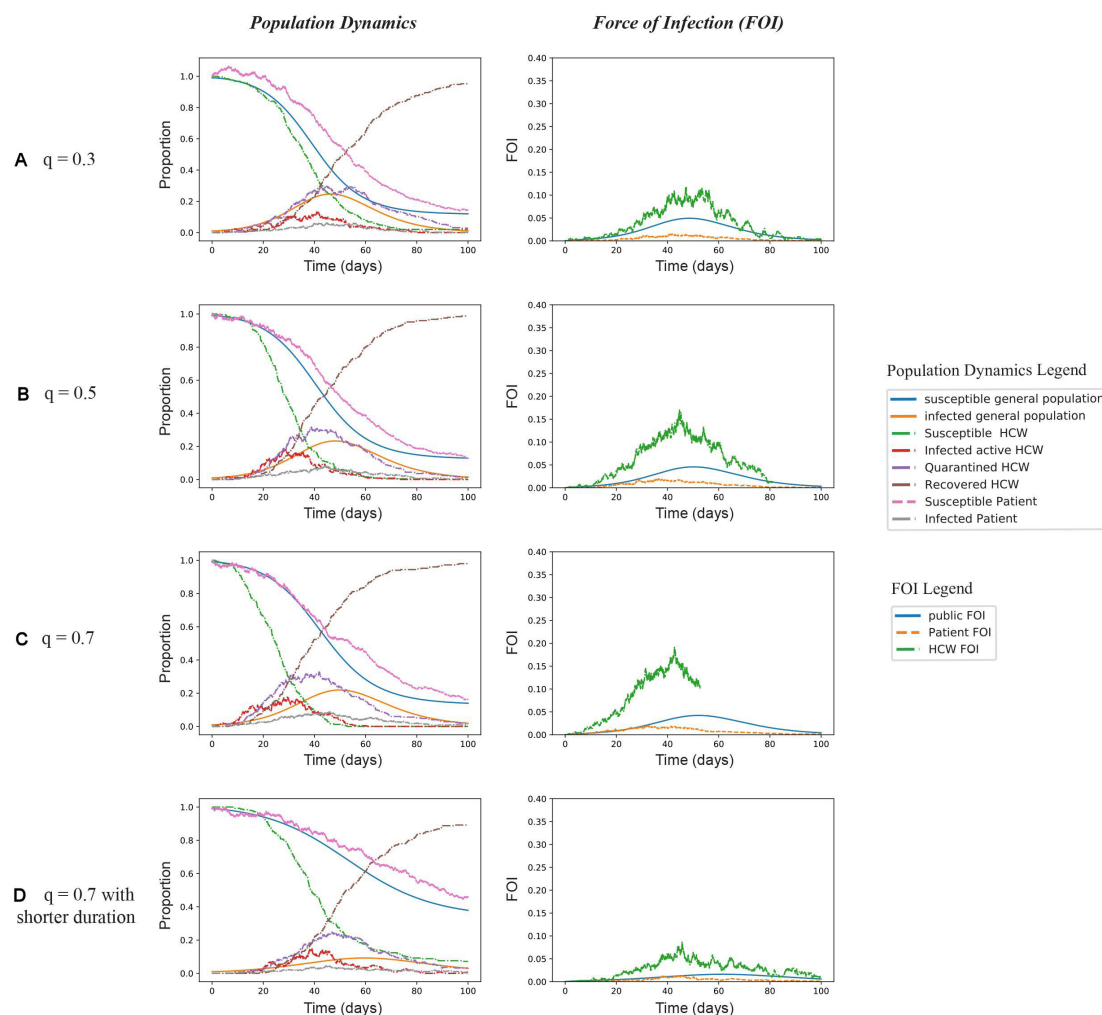


Figure 3 Comparison of scenarios with varying proportions of asymptomatic infections (q). Here all scenarios have a testing rate $\omega=1/7$. The asymptomatic proportion was changed from the default value of $q=0.5$ in (B) to a lower value of $q=0.3$ in (A) and then to a higher value of $q=0.7$ in (C). To explore the impact of potential shorter duration of infectiousness of asymptomatic infections, the parameter of γ_A was changed from the default $1/9$ to $1/5$ with $q=0.7$ in (D). We find that the increasing proportions of asymptomatic infections can increase the peak of infected HCWs and patients, increase the FOI and reduce the peak of quarantined HCWs. However, the duration of infectiousness of the asymptomatic has larger impacts, where under the higher proportion $q=0.7$, if the duration of infectiousness is shorter, the peak of infections and FOI can substantially reduce. FOI, force of infection; HCW, healthcare workers; PPE, personal protective equipment.

Whether infection comes in through an externally infected HCW, a visitor or an asymptomatic/presymptomatic, new infection does not significantly affect the outcomes. As long as the within cohort reproduction number (online supplemental appendix B) is greater than 1, once the infection is established in the cohort, the dynamics will be dominated by the internal infection process.

DISCUSSION

COVID-19 presents an unprecedented challenge throughout all healthcare systems. The pronounced increases in the risk of severe disease or death that are found in older age groups, as well as patients suffering comorbidities, demands that these at-risk groups be protected. And yet they are also disproportionately likely to require healthcare for conditions other than

COVID-19. Contact and risk to these high-risk groups can be reduced by innovations such as telemedicine consultations for chronic conditions, but urgent care will continue to be needed in acute cases and higher demands of healthcare will happen in the seasons of high respiratory infections. Therefore, this work has been an attempt to evaluate the roles of cohorting, prompt and accurate diagnostic testing, and PPE in protecting patients and HCWs, in order to propose the most effective measures to protect individuals in healthcare settings even with scarce resources.

Our primary finding is that though the relative impacts of interventions depend on the underlying properties of the disease and in particular infection from currently asymptomatic/presymptomatic individuals, PPE, mainly referring to facial masks in this study for practical implementation, is the most effective approach to reduce

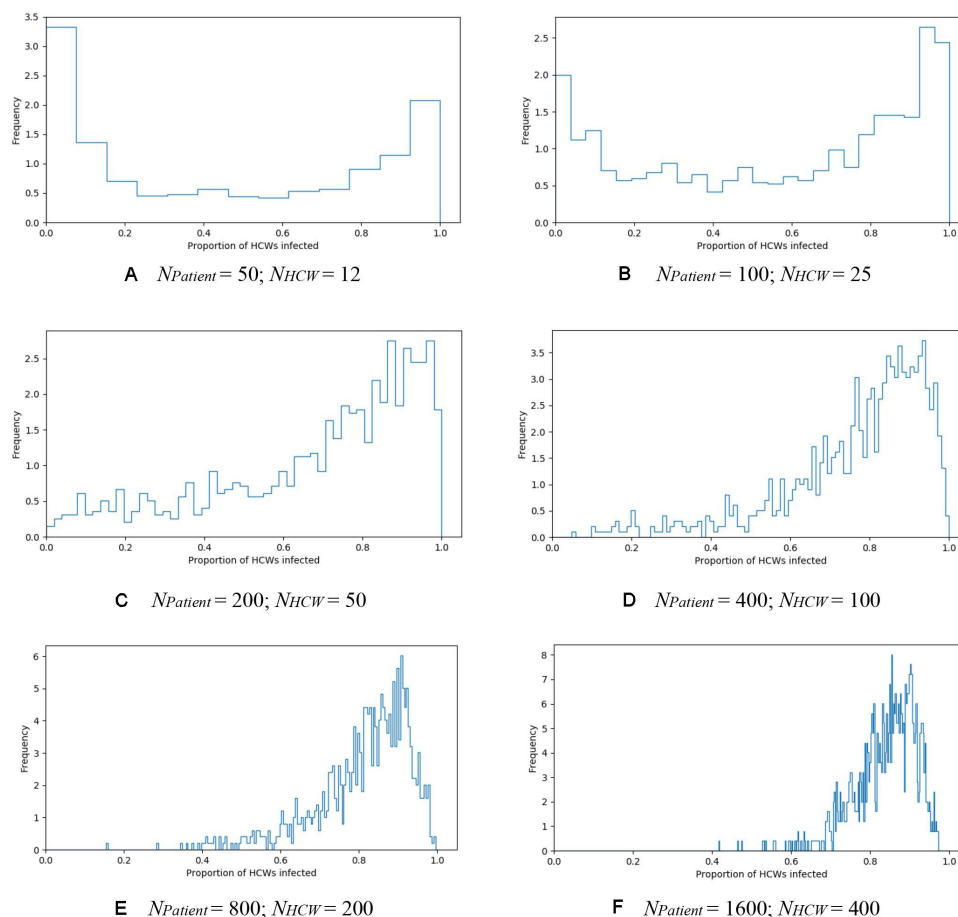


Figure 4 The impacts of cohort size based on 1000 simulations per cohort size. Probability density of outbreak sizes for different cohort sizes is demonstrated. Each cohort keeps a patient:HCW ratio as 4. As the cohort size increases, the frequency of small outbreaks goes down and the frequency of large outbreaks goes up. With large cohort sizes, all cohorts have outbreaks that infect a large fraction of people. With small cohort sizes, many cohorts have no outbreaks, or outbreaks that only infect a few.

the FOI for all cohorts, compared with regularly viral testing. The possibility of asymptomatic transmission has been apparent for some time and it has recently been confirmed to be responsible for a large fraction of transmission events.^{18 24} We find that it makes little impact on the FOI (with the caveat that it depends on the duration of the asymptomatic period), but it magnifies the impact of effective PPE. The potential transmission from presymptomatic individuals has long been known to be a crucial component, as it largely increases the difficulty to control an infectious disease.²⁵ This model confirms that if we wish to prevent SARS-CoV-2 transmission in the non-COVID cohort, all individuals should be assumed to be infectious, both HCWs and patients. Where appropriate PPE is available, it should be widely used throughout healthcare, and indeed the use of cloth masks is now recommended for the general public by the Centers for Disease Control. However, ample PPE may not continue to be available in all settings, and PPE for the non-COVID cohort is an important element of planning. Notably, the impact of weekly random testing of HCWs and patients in the non-COVID cohort is unable to prevent infection from becoming established in the absence of other

interventions. Furthermore, in many locations testing is not only infrequent, but also testing results are not available in a rapid turnaround to take timely preventions. The testing delay is expected to become more severe as prevalence increases in the community and in healthcare settings. These findings on PPE and viral testing are also relevant to resource-limited settings where testing may not be widely available, or anywhere a tradeoff exists between testing and PPE.

Another important finding is regarding the size of subcohorts—by keeping subcohorts smaller, we can reduce the probability that infection establishes. If infection reaches a cohort, the introduction may fail to establish itself. However, modelling shows that when an infection does establish, it tends to have an increased early growth rate.²⁶ Mathematically, this can be interpreted as a consequence of the fact that if on average a small outbreak would grow by a factor of R_0 at each generation, but some go extinct, then those that do not go extinct must have increased transmissibility in order to achieve the observed average.²⁷ This means that interventions that increase the probability of causing 0 transmissions from an introduction are of particular importance.

In the presence of a very high FOI from the community at large, they are of less value compared with interventions that reduce R by more. However, in combination with a sustained effort to prevent the introduction of infections (and at the initial stage of the pandemic), smaller cohorts in which HCWs are divided into smaller groups with no intragroup interactions may have value in preventing establishment of the infection in the healthcare setting. Moreover, this work does not model any attempted mitigation strategies in the community at large to reduce the FOI. In the presence of community mitigation strategies, the value of subcohorting is expected to be enhanced. While cohorting is understood to be important,²⁸ subcohorting has so far received less attention. Our findings suggest that this can be an important strategy, especially in combination with community mitigation strategies and in settings where PPE and testing may be in short supply.

There are several important elements of the COVID-19 pandemic and SARS-CoV-2 biology that are not captured by our model. We have assumed an unmitigated outbreak outside the non-COVID cohort, which is not the case in most locations; that is, the model is deliberately general and does not include potentially important factors (such as non-pharmaceutical interventions—physical distancing or salutary sheltering) influencing the course of the pandemic outside healthcare, which will determine the number of times that the virus is introduced to the non-COVID cohort. However, much of the most important dynamics we observe happen early on, and so our findings will be relevant independent of the details of the pandemic outside. We also do not directly model the consequences of transmission in the healthcare setting; obviously transmission to elderly patients or otherwise vulnerable individuals is expected to have an outsize impact on overall mortality and the strain on healthcare in general. We have also not considered the consequences of an overdispersed R_0 . The SARS-CoV-1 outbreak, as well as MERS outbreaks have both been characterised by super-spreading events in healthcare settings.^{29 30} SARS-CoV-2 has also demonstrated overdispersed R_0 , with 19% of the cases seeded 80% of the transmissions.³¹ Though we do not model overdispersion explicitly, it would be expected to increase the impact of the subcohorting strategy by limiting the total potential cluster size, because it is known that an overdispersed R_0 can lead to situations in which most disease introductions go extinct.²⁷ Finally, we have assumed some conditions on the testing and the COVID-19 symptomatic monitor: (1) viral testing is accurate, while in reality sensitivity likely depends on the stage of infection or the viral load dynamics during the course of the infection;³² (2) testing continues at a constant rate in the cohort, which neglects an enhanced level of testing that might be expected if an infection is detected and (3) all patients and HCWs are monitored closely enough that individuals are immediately identified once symptomatic.

As communities around the globe confront the pandemic, the most important way to reduce transmission in healthcare settings is to ensure an adequate supply

of PPE to reduce transmission. Testing, especially rapid testing, should also be made available both to identify those who are infected and those who have been infected, and innovative approaches will need to be taken to minimise the pandemic threat. Subcohorting within institutions is a simple and potentially underutilised approach that could also help reduce healthcare transmission, especially in lower incidence settings and in combination with strategies to mitigate the pandemic in the community at large. We hope that our analysis will motivate future action to preserve lives.

Twitter Xueting Qiu @XuetingQ, Joel C Miller @joel_c_miller and William P Hanage @BillHanage

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Contributors XQ searched literature, conducted the analysis, visualised and interpreted results, wrote and edited the manuscript. JCM conceived of the study, conducted the analysis, visualised and interpreted results, wrote and edited the manuscript. DM searched literature, wrote and edited the manuscript. WPH conceived of and supervised the study, interpreted results, wrote and edited the manuscript.

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Data availability statement Data are available in a public, open access repository. All data relevant to the study are included in the article or uploaded as supplementary information. This study takes a pure mathematical modelling approach to examine the impact of different strategies, based on parameter estimates drawn from the literature. All relevant parameters and their values are included in the tables. The Python scripts for the modelling simulations are available at <https://github.com/joelmiller/HospitalCOVID19>.

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ORCID iD

Xueting Qiu <http://orcid.org/0000-0001-6810-7304>

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