Digital contact tracing: comparing the capabilities of centralised and decentralised data architectures to effectively suppress the COVID-19 epidemic whilst maximising freedom of movement and maintaining privacy.

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Introduction

The aim of contact tracing is to provide an early warning to people that they have come into contact with someone who may be infected with COVID-19. Receiving this warning means that people can take action to prevent spreading the virus onwards, especially to vulnerable people. This action may involve quarantine for a number of days, or could be just an increased level of awareness, hygiene and physical distancing.

Digital contact tracing has the potential to assist people in receiving this warning as quickly as possible, before they become infectious. This speed advantage of a digital process is particularly important for COVID-19, where the virus is in many cases spread before people develop characteristic symptoms. Digital contact tracing may also help notifications reach people who otherwise wouldn't be recalled, such as people who have shared a space on public transport.

The aim of this report is to provide an overview of different considerations in the design of systems for digital contact tracing, and to address recent controversies that have arisen in the choice of possible architectures for digital contact tracing. The choice of architecture should be informed by considerations of what the system is trying to achieve. The aim of the intervention is to 1/ contribute to maintaining ongoing control of the epidemic as part of an integrated Test, Track and Trace strategy 2/ Minimise the number of individuals whose lives are disrupted by requests to isolate, distance, or quarantine whilst maintaining epidemic control 3/ Minimise the invasion of privacy needed to achieve aims 1 and 2.

Epidemiological and public health requirements for a COVID-19 contact tracing app

Digital contact tracing apps are a key component of many national strategies for suppressing COVID-19. Designing an effective app requires expertise from diverse fields including information security [Vaudenay, 2020], ethics [Morley et al. 2020; Parker et al. 2020], and behavioural science [Abeler et al. 2020; Altmann et al. 2020]. For these apps to achieve their core purpose of stopping COVID-19 transmission, epidemiological considerations must be at the heart of their design. We present five key epidemiological and public health requirements which COVID-19 contact tracing apps should satisfy:

1. Sensitively and specifically identify infectious individuals

The purpose of contact tracing apps is to send notifications only to potentially infectious individuals. Failure to send notifications to infectious individuals by missing meaningful contact events, and falsely sending notifications for non-infectious individuals, should both be minimised. This means minimising both the number of false positives and false negatives in Table 1.

Table 1. Four outcomes of the contact tracing process:

All contacts	**Infected**	**Not infected**
Notified	True positives	False positives
Not notified	False negatives	True negatives

To achieve this, the algorithm must be **adjustable**. In this rapidly developing epidemic, our knowledge of the disease is continuously improving. It may vary across populations and social networks, and over time through the impact of interventions such as school closures. To fix an algorithm before the app is released, with no capacity for change, is to risk locking the app in a state of poor performance.

If an individual has erroneously received a notification instructing them to quarantine, either from malicious use or an index case reporting symptoms but later receiving a negative test result, it should be possible to send them an **early release notification**. If an individual has received a quarantine notice following contact with more than one index case, release should only be given if all index cases are confirmed to be uninfected.

2. High user uptake and adherence

Even at low levels of **uptake**, apps can reduce transmission and have a protective effect on the population, including those without smartphones [Hinch et al. 2020]. However, achieving epidemic control in the **absence** of other strong interventions will typically require uptake by around 60% of the population. Once installed, an app will only affect the epidemic if users follow the instructions it issues. Trust in the app and a positive user experience are therefore essential components for digital contact tracing to be effective. Any design choices which could hinder **adherence** should be avoided, such as frequent erroneous notifications. Further, in order to resume travel without increasing the risk of epidemic resurgence, apps should be **interoperable** across public health regions. Without this, users would have to install multiple apps, with a likely detrimental effect on accuracy, uptake, and adherence.

3. Rapid notification

The time between onset of symptoms in an index case and the quarantine of their contacts is of key importance to COVID-19 contact tracing; any delay reduces its effectiveness [Ferretti & Wymant et al. 2020] and delays much beyond 2-3 days, reach the majority of contacts after they have infected others, removing all public health benefit entirely. Where a design feature introduces a short delay, such as awaiting test results, it should only be implemented if the delay is outweighed by other gains such as in specificity, uptake, adherence, etc. The relative impacts of these factors should be quantitatively compared at the design stage in open-source models such as [OpenABM-COVID-19].

4. Integration with local health policy

The advice given by an app notification should be adjustable to remain consistent with current local health policies. Ideally the app should be integrated within the full range of public health interventions such that it serves as a link to accessing further advice, medical care and testing.

5. Ability to evaluate effectiveness transparently

Users must be confident that notifications are based on the best available evidence. The contact tracing algorithm should therefore be transparent, auditable, under oversight, and subject to review. Any intervention in an epidemic should be evaluated, both alone and in combination with other measures. Multiple independent approaches should be used in these evaluations and the metrics of success and failure should be decided upon in advance.

Aggregated data (not linked to individuals) is essential for evaluating and improving the performance of the app. Although some such information could perhaps be gained via surveys, there are strong practical and ethical justifications for gathering these data via the app itself. These justifications are particularly concerned with the speed and scale of the epidemic, and the huge social and economic costs of failing to control it.

- **Instantaneous summary statistics**
  Summary statistics such as the numbers of index cases and contacts should be available. This data will be crucial for evaluating the app and rapidly identifying malfunctions or malicious use, as well as being extremely valuable for public health planning.

- **Geographical summary statistics**
  Knowledge of local uptake is vital for assessing the app's effectiveness and the reliability of its evaluation of individual risk. Without this, individuals in areas with low app uptake and high incidence of COVID-19 could erroneously be given the impression that they are at low risk, especially if there is an inverse correlation between epidemic growth rate and app uptake.

Summary of different proposed data architectures

Several architectures have been proposed for digital contact tracing, and there has been some controversy on which is the best choice. So far the debate has centred on privacy considerations which are an important - but not the only - ethical consideration in designing digital contact tracing [Parker et al. 2020].

There are broadly two classes of architecture, the so-called centralised architecture, and the decentralised architecture.

In the centralised architecture, the process of passing information from the individual who is ill to their contacts is mediated by a central server. The central server allocates IDs to individual phones. When an individual is diagnosed with either suspect or confirmed COVID, their contact history is uploaded to the server. The server performs some computations, and based on those computations, notifications are sent to some of the contacts.

In the decentralised architecture, the process of passing information from the sick individual to their contacts is done through direct broadcasts of lists of sick individuals over the phone network. Each phone then regularly does a computation to determine whether the phone has been associated with a risky contact with one of the sick individuals. Decentralised systems use a central server for updating tracing rules, and for collecting aggregate summary statistics.

Each specific implementation may use one or the other, and may mix elements of both. Broadly, the NSHX COVID-19 App uses a centralised architecture, and Google/Apple and D3PT both use a decentralised architecture. Google/Apple perform calculations in the operating system passing summaries to the App they support, whereas D3PT performs computations in the App.

Here, we propose an assessment based on our current understanding of these architectures. Proposed solutions are evolving and our assessment will continually update as more details appear.

Summary assessment

Many of the basic tracing functionalities are similar between the centralised and decentralised systems, including the ability to report aggregate data.

There are three important differences that favour the centralised model, and three that favour the decentralised model.

Benefits of centralised systems

1. Evaluation, learning and improvement of the notification process

Consider the following scenario. A passenger infected with COVID-19 gets on a bus and sits down next to someone. There are 15 other people on the bus. Some are sitting closer to the infected passenger, than others. This information will be recorded by the apps. Are all passengers at risk of being infected, or just the person sitting next to the infected passenger? Both the centralised and decentralised apps can be tuned to reflect different assumptions. However, by analysing the contact patterns submitted anonymously by all infected users, the centralised app will be able to answer this question so that future alerts can be more precisely targeted, thus reducing unnecessary notification, and also reducing infections, protecting hospitals and saving lives. The decentralised app will not be able to learn how to make alerts more or less targeted.

At present, not enough is known about the spread of COVID to make sure that the initial configuration of the apps (centralised or decentralised) strikes the right balance between notifying too many people (all the people on the bus in the example above), or too few (just the person sitting next to the infected person. Being able to evaluate, learn and improve the app, which can only be done by analysing a central database, will allow the app to quickly improve in the first few weeks of use.

One possible solution to this problem in the decentralised model is to ask many users to 'donate' their data on a regular basis. However this may result in more privacy problems than the centralised server, and is not currently possible with the architecture developed by Google and Apple, nor is it expected to be implemented in the future.

2. Safe notification based on self-reported diagnosis.

With the centralised model, it is possible to allow notifications to be sent based on self-reported diagnosis, and to later update these notifications based on testing results. This means that individuals could receive an Amber notification that they have been in contact with a suspect case of COVID. This would be upgraded if the case becomes positive, to a Red notification that the person has come into contact with a case, or removed if the person tests negative. Because

COVID is transmitted before people develop symptoms, the speed of notification is critical to the control of COVID.

In a decentralised system, self-diagnosis would present a security risk to the system, since it would be more open to abuse - anomalous patterns of self-reporting could not be detected and blocked in a timely manner and malicious attack could result in uncontrolled cascades of notifications

Given current turnaround times for testing, a decentralised system as proposed is predicted to contribute minimally to the control of COVID transmission.

3. Notifications based on the time since start of symptoms in the infected case.

People are not equally infectious throughout all stages of infection. People are most infectious near the start of onset of symptoms. Infectiousness typically starts about 2 to 3 days before and continues 2 to 3 days after (possibly longer in some individuals). In the centralised system, it is possible to rank contact events so that contacts that took place close to the onset of symptoms are more likely to result in notification. In the decentralised system, the notifications are based on the information about the person who is receiving the notification, not information about the person who has just been diagnosed. This means that unless this additional information is broadcast, in the decentralised system there is a greater risk of false positive and false negative notification.

Benefits of decentralised system

4. Support by owners of the operating systems

Google and Apple run the operating system that runs on most smartphones. Through their operating system and an API, Google and Apple will provide enhanced support for apps that use this API, and such apps must be decentralised. Decentralised apps will benefit from stability under upgrades of the operating system, and may benefit from improved support for bluetooth functionality. Use of Google and Apple systems may increase interoperability with other apps based on the same API. In the medium term, Google and Apple may include detection and recording of contacts in the operating system, such that an App would have access to a history of contacts even if only installed once symptoms of COVID initiate, which would potentially be a substantial benefit in terms of coverage.

5. Increased privacy

Increased privacy is an intrinsic benefit of the decentralised system, and may also have the additional benefit of increased uptake of the app. Increased uptake of the app will increase the efficacy of the intervention, provided the notifications can be sent in a timely manner (within 48 hours of symptom onset, ideally before), and provided the tracing algorithm is tuned to send notifications based on the correct measure of effective contact.

Summary of the trade-offs

6. Trade-offs in privacy, efficacy, and false positive notifications

In summary, the centralised system preserves information on contact events between individuals, one of whom is a diagnosed case of COVID. The information consists of pseudonymised IDs of both the case and their contact, as well as some information on the case: date of diagnosis, age band (to 10 years), time since onset of symptoms (in days), and first four letters of the postcode. The contact events themselves consist of signal strength for bluetooth.

For the decentralised system, similar data would be stored from cases, except for the details of the contact event. Analysis of the details of the contact event will be useful in stratifying risk of infection, and identifying infectious individuals before they transmit to others, with greater accuracy.

Both systems preserve much less information than manual contact tracing (where data is manually entered into a central database by a phone operator), though in manual contact tracing consent to record information about contacts is not obtained from both parties. Both systems can therefore be considered an improvement, in privacy terms, over established public health practices.

The loss of privacy associated with this extra information from the centralised system would be traded off for 1/ the capacity to send notifications quickly, which would reduce the risk of new infections and increase the chance of new infections 2/ the benefits of learning a better model of whom to send notifications to, reducing the number of false positive and false negative infection. Both of these capacities would increase the efficacy of the system in contributing to the control of the epidemic (saving lives), and to reducing the risk of people being falsely notified that they are at risk of being infected, and being asked to self-isolate or quarantine.

Both systems collect data, and distribute notifications that impose restrictions on civil liberties. Neither system is justifiable unless it's benefit can be shown. Fatal flaws facing either system must be solved before release. For example, if decentralised contact tracing can only be initiated on a positive test, and test turnaround times cannot reach speeds necessary to trace the majority of people before they transmit to others.

Some unanswered questions that arise from this trade-off are
1/ whether any practical system exists that can be designed in a timely manner that combines advantages of both systems and has fewer disadvantages than either, or which of the existing systems can most quickly converge on this system;

2/ whether the benefits in terms of potential uptake for a decentralised system, and the operating system support offered by Google and Apple make up for the disadvantages of the decentralised system in terms of lack of control on false positives, false negatives, and delays introduced into the process of notification. For current testing turnaround times in the UK, these delays could make a difference between controlling the epidemic, or not, irrespective of uptake;
3/ conversely, whether the privacy concerns associated with the centralised model can be mitigated by appropriate oversight.

Detailed assessment

Receiving notifications that one has been in contact with someone infected with COVID is a disruptive event, it may cause concern, anxiety, and will lead to difficult and disruptive choices as to whether to self-isolate, work from home where possible, and reduce contact with family, friends, or engage in care of others. Similarly, not receiving notifications because a contact was judged low risk for transmission carries the potential for significant harm, since a person may infect others during the period when they could have been notified. The process of deciding who does and doesn't get notified given a history of contacts is central to contact tracing. Evaluating and improving this process is imperative to the correct function of contact tracing.

Concerns have been raised about the potential for digital contact tracing to invade the privacy of those who participate in contact tracing; for the process of contact tracing to be associated with coercive measures, e.g. compulsory use of the system, or coercive monitoring of individuals with the system; for digital contact tracing to leave a negative legacy of increased digital surveillance by states, especially through mission creep and misappropriation of identifiable data.

These are legitimate concerns. Two complementary approaches may be taken to mitigate these risks. One is to design systems that are less liable to being misused. The second is to engage a system of oversight, both by representatives of democratic institutions, by review and oversight boards, by compliance with data protection laws (generic and specific) and by choosing designs that minimise the risk of long-term harm from digital contact tracing.

Both centralised and decentralised digital-contact tracing in practice require both parties in a contact event to consent to it being recorded, which is not true of the central databases used to support manual contact tracing. A comparison with manual contact tracing is worthwhile. In manual contact tracing, individuals are interviewed by contact tracers after they become a case on the people they have contacted and the places they have been. These data are digitally centralised, including personal data on contacts who have not consented to be listed. Contact tracers then follow up on the information given, usually over several days, and pass on information to those at risk of having been infected. In sexual health medicine partner notification requires records to be kept of multiple linked-anonymised patient identifiers alongside extremely sensitive personal data. In comparison, digital contact tracing relies on the informed consent of all parties involved, and even centralised versions of this system reduces the need to link patient identifiers with sensitive clinical and demographic data that routinely occurs in manual contact tracing. On the other hand, manual contact tracing will always be limited in scope due to its laboriousness, and it is easier for people to understand what the process is.

The issue of long-term legacy seems important too. Currently, there could be argued to be poor understanding of issues around privacy and consent on phone apps, and few people are aware of the collection, cleaning and re-sale of data that is widespread. There is some fear that digital contact tracing could lead to a continued deterioration of standards of privacy. Conversely, for many people, it may be the first time they explicitly consider the issue of data use at the population level, in which case it could be a welcome opportunity to have an overdue wider discussion of this important topic.

Done badly, digital contact tracing could set a precedent for increasing the use of digital technologies to reduce the privacy of individuals. Conversely it could be argued that exposing a wider proportion of the population to the issues of privacy, in the context of a public health intervention where data are pro-actively shared to help save lives, might facilitate a wider post-pandemic discussion of what is or isn’t appropriate use of private data collected digitally, and help avoid the most egregious abuses of privacy that are already widespread.

The increased concerns around privacy of digital contact tracing compared to digitized manual contact tracing seem focussed predominantly on the ease with which relational data can be collected. Concerns about privacy need to be considered alongside the potential benefits of digital contract tracing and evaluated on grounds of proportionality. Specifically, digital contact tracing offers two benefits - (i) the intervention aims to save lives, and within an integrated public health system offers something that manual contact tracing cannot - and (ii) the intervention allows return of social freedoms , that blunter interventions, such as mass isolation (lockdown) have taken-away. Individual users, and society in general, will expect their data is used optimally in pursuit of these aims. In real terms this equates to accurate prediction of infection-risk, appropriate advice, and minimal amounts of disruption from inappropriate advice (eg, from false-positive and false-negative notifications).

The system should be as privacy-preserving as possible within these constraints.

Two broad classes of data architecture have been proposed for digital contact tracing, the decentralised model favoured by Google and Apple in their joint API, and the D3-PT consortium and being adopted by the public health systems of Switzerland, Austria and Germany and the centralised model favoured the public health systems of the United Kingdom, France, Norway and Australia. The purpose of this document to compare and contrast these different approaches to achieve maximum benefit, in terms of epidemic control with minimum disruption to society, in a privacy preserving manner

First, we address an issue of nomenclature: both these systems will operate ideally only when integrated within a public health response, such that messages can be reinforced by human operators, and such that the notifications can be reinforced and linked to a testing system. Furthermore, manual contact tracing will be needed to complement poor app uptake and address issues of digital exclusion. Both the systems will require many users to voluntarily upload data to a central database for the integration into a public health response. Both systems will need to be audited in terms of number of cases and average number of notifications per case to ensure correct functionality, and both systems will rely on parameters for the tracing algorithm that should be supplied by a central server so that the tracing policy can remain coherent with the local public health response. All of these points have been agreed for all the platforms under discussion.

Therefore the comparison is not one of one system having a central database in the public health system, and the other not, it is rather the question of which data are stored in the central database, and which data remain on the phones of users.

The principal difference between the two systems is that relational data, those that record parts of the contact graph, is proposed to remain on phones in the decentralised system, and is to be partly uploaded on the central server in the centralised system. In both cases, these relational graphs involve pseudonymized identifiers. In the decentralised system, no linked pairs of pseudonymized identifiers indicating a past contact event may be uploaded to the central database. Beyond that, both systems will rely on voluntary uploading of aggregated data about an individual's exposure to risky contacts for the correct functioning of the system and integration into the public health response.

Having discussed generalities, we now address a technical comparison of both systems in terms of how the notification procedure works, and how it may be evaluated and improved in both settings.

The setting

Consider a population of N individuals, labelled i=1,...,N, each equipped with a phone running a digital contact tracing app. Let $X_{i,t}$ be information about individuals that they can choose to share with a central server when requested. Examples include gender, partial postcode, nature and severity of symptoms, a score indicating relative vulnerability, test results, etc.

Let $G_{ij,t}$ be the history of contacts between individuals i and j up to time t. The history may be deleted with a rolling average. The history may be obfuscated using pseudonymized IDs.

Let $N_{ij,t}$ be the history of notifications received by individual i up to time t relating to prior contact with person j. The history may be obfuscated by using pseudonymized IDs.

Under all systems, the phone of user i stores the full list {i, $X_{i,t}$, $G_{ij,\,t}$, $N_{ij,t}$ for all j}. The list will be pseudonymised with respect to j, and j may have provided ephemeral pseudonymised IDs such that, from i's point of view, it will not be possible to see whether contacts are with the same or different people.

Identifier-stripped contact lists

Let $G_{ix,t}$ and $N_{ix,t}$ be the versions of $G_{ij,t}$ and $N_{ij,t}$ where the contact identifiers j have been removed and replaced with unlinked labels.

The system can only be called truly anonymised if it is not possible to reconstruct $G_{ij,t}$ and $N_{ij,t}$ from $G_{ix,t}$ and $N_{ix,t}$, which in general will not be the case.

Contact tracing

Centralised system

Under the centralised system, when the individual i is diagnosed with COVID at time t, they are asked to upload their history {i, $X_{i,t}$, $G_{ij,\,t}$ for all j} to the central server. At a minimum, the server contains the list of entries uploaded from diagnosed cases. An algorithm f_k regularly scans the database, with a functional operation we denote f_k({i, $X_{i,t}$, $G_{ij,\,t}$ for all j}) to generate a set of notifications at time t. The index k denotes that the chosen algorithm is one of many (probably infinite) set of possible algorithms. Running the algorithm generates a new set of notifications $N_{ij,t+1}$ that can be pushed or pulled to the relevant users, and are only stored on the central server.

Decentralised system

Under the decentralised system, when the individual i is diagnosed with COVID at time t, they are asked to broadcast their list of pseudonymised versions of their ID i to all other users, via a central server, for a specified amount of time. Let $D_{j,t}$ be their history of diagnosis that is stored on all other phones. Based on this broadcast, all other users i run an algorithm g_k({j, $D_{j,t}$, $X_{j,t}$, $G_{ji,\,t}$, $N_{ji,t}$ for all j}) to update their own notification $N_{ji,t+1}$, where g_k is one of many possible algorithms, which can be downloaded and updated from a central server at regular intervals.

Crude comparison with regards to privacy and effectiveness

The decentralised system does not rely on uploading any individual data to a central server, and is tuneable, in the sense that a central server can supply a function g_k.

In its basic form, the decentralised system, while maximally privacy-preserving, does not supply any information that would allow a public health system to know how many cases arose, how many notifications were received, or to allow any assessment of the suitability of the tracing algorithm g_k, in terms of its two main functional benefits namely numbers of infections prevented and lives saved, and individuals freed from unnecessary isolation or lockdown.

The basic security and privacy assessments of these systems should be made by experts, which we are not. Centralised and decentralised systems each have different vulnerabilities to security breaches, explored elsewhere. Those are critically important considerations, but not the subject of this report.

An asymmetric epidemiological difference between the systems

The core algorithmic steps for the centralised system, f_k({i, $X_{i,t}$, $G_{ij,\,t}$ for all j}) and decentralised system, g_k({j, $X_{j,t}$, $G_{ji,\,t}$, $N_{ji,t}$ for all j}), are not equivalent, since the former uses covariates $X_{i,t}$ of the person who has been diagnosed with COVID, whereas the latter uses covariates $X_{j,t}$ of the person who has come into contact with the person with COVID.

(Use of the covariates of the contacts is not done in the centralised system, because only index cases upload contact data, not all individuals or notified individuals. This could be changed by asking notified individuals to donate data, but is not planned by any system as it would rapidly build a social graph without clear utility.)

So for example supposing Alice has been in contact with Bob 5 days ago, and Bob is now diagnosed with COVID. For the centralised system, the tracing algorithm can account for the age group, gender, time since symptoms, etc. of Bob, whereas for the decentralised system, the tracing algorithm can account for the age group, gender etc. of Alice. Which approach is better depends on which set of covariates is better for predicting whether transmission is likely to have happened or not. Currently, the three best established predictors of transmission are 1/ time before or since onset of symptoms of the index case, 2/ severity of symptoms of the index case and 3/ age of the contact. This gives a small accuracy advantage to the centralised system, since two of the three predictor depend on the transmitter, and the effect sizes are larger.

Data donation

Centralised system

Under the centralised system, individual i may choose to donate their history {i, $X_{i,t}$, $G_{ij,\,tt}$ for all j} to the central server for additional assessments. It would also be possible to augment the variables $X_{i,t}$, though this is not discussed here.

Decentralised system

Under some configurations of the decentralised system, individual i could choose to donate their history {i, D_t , $X_{i,t}$, $G_{ix,t}$, $N_{ix,t}$ for all j} to the central server for additional assessments. It would also be possible to augment the variables $X_{i,t}$, though this is not discussed here. Most implementations would discourage this, or reduce it to aggregate statistics. (Individual specifications will vary, for example some systems may not allow time stamped histories $G_{ix,t}$ to be uploaded.)

Comparison with regards to privacy

The decentralised system is only privacy enhancing if the lists $G_{ij,t}$, $N_{ij,t}$ cannot be reconstructed from $G_{ix,t}$, $N_{ix,t}$. Critically, under the centralised system consent to donate data to a centralised system is obtained for all users of the system at enrollment (on-boarding) and no additional consent needs to be sought to ensure (and optimise) effectiveness and safety of the system. Conversely, if safety and effectiveness of a decentralised system is reliant upon a subset of individuals choosing to concede less privacy in order to benefit the system overall, this raises ethical questions of fairness.

Evaluation

General concept
Each time-step, each system issues a new set of notifications based on the tracing functions f_k and g_k , respectively, that process the contact history G_{ij} . These notifications are predictions that, if person i is diagnosed at time t, that person j is now likely to be infected (and so infectious), or not. A perfect system will issue notifications only to those infected, and not to those not infected. No system will be perfect, due to the stochasticity of virus transmission and imprecision in the risk calculation: Some individuals will be notified even though they were not infected, thereby disrupting their lives (false positives), and other individuals will not be notified even though they were infected, so missing an opportunity to inform them of the risk they pose to others (false negatives). A system that minimises false negatives can contain the epidemic if widely used, but may result in so many notifications that it becomes discredited (‘boy who cried wolf’) and may be less equitable and equally costly than rolling lockdowns (Hinch et al, Report 3). The credibility and utility of a tracing system therefore rests on being able to evaluate false positive rates and false negative rates (Table 1), that should be made public for transparency.

This issue is separate from other important evaluations which affect the outcome of the digital tracing policy, such as uptake of the app, user adherence, integration with testing and other public health measures. It is linked to engineering performance, conditional on any signal having been exchanged at all.

Centralised system

A possible schema for evaluating the tracing function f_k goes as follows. For each individual i declared a case at time t, for each subsequent time t+1, t+2, t+3,..., consider how many of the individuals j contacted by case i (non null entries in $G_{ij,s}$ s<=t) themselves become a case. Separate these into those that were notified and those that were not. Model the follow up process to correct for background infection and notification rates. Output is an estimate of the four entries of table 1 for the tracing function f_k at time t.

Decentralised system

Two possible schemas for evaluating the tracing function g_k , involving data donation, go as follows.

Schema 1. For each notified individual j notified of being a contact at time t, ask them to donate their history {i, $D_{x,t}$,$X_{i,t}$, $G_{ix, t}$, $N_{ix,t}$ for all x}. At a later date t+m, ask them whether they have developed symptoms (or perhaps more simply ask them to upload their own notification history $N_{jx,t}$), and to donate this information. With this information it is possible to estimate only the top row of table 1.

Schema 2. For a sample of individuals j ask them to donate their history {i, $D_{i,t}$,$X_{i,t}$, $|G_{ix, t}|$, $|N_{ix,t}|$ for all x}, and to donate information on whether they have experienced symptoms in the last m days, and whether they had been notified or not at the time of sampling. With this information, it may be possible to evaluate whether exposures to each diagnosed individual i led to a correct notification, with modelling to evaluate the case of multiple exposures, this leading to estimates of the whole of table 1. At this point, no clear schema for evaluation has been developed for evaluation of decentralised systems, and details of what is possible will vary depending on specific choices. In some variants of the decentralised system proposed, only the size of sets $G_{ix, t}$ and $N_{ix,,t}$ and not the linkage between them, which is needed to evaluate the tracing function.

Iterative improvement

By simulation, it is possible to find the desired sensitivity and specificity that maintains epidemic control (contributing to keeping R<1, maintaining the right to life) and that minimises the number of false positives (maintaining the right of movement). Note that in extremis, curtailing the right to movement may cost lives, such that trade-offs may need to be considered.

At this stage, it is possible to computationally test arbitrarily many functions to find the best next function f_{k+1} or g_{k+1} . Both centralised and decentralised systems will allow setting-specific and changing functions over time.

Rapid convergence will ensure closest adherence to values that keep R<1 whilst minimising false positives. Convergence is possible for the decentralised schema 1, but will be slower than the centralised schema or the decentralised schema 2.

Summary assessment

With the pure decentralised model, no evaluation or optimisation is possible using data internal to the system. Evaluation would involve detailed study of many users of the app, and construction of a new centralised database of app users, with extensive epidemiological questionnaires.

Unless other measures are in place to keep $R<1$, this architecture can be said to have placed the right to privacy above the right to life and the right to movement. If other systems are in place to keep $R<1$, the system is not needed, and privacy would be best preserved by not engaging in digital contact tracing. The system could be justified in marginal cases, where $R>1$, and some external metrics are kept to see that the number of notifications is e.g. comparable to manual contact tracing, and an external database is constructed e.g. by phone interviews, to see that the false positive rate is acceptable. For comparison, the false positive rate for contact tracing is approximately 85% to 95% of those notified.

With a centralised model, and with the decentralised model with large data donation (schema 2), it is likely to be able to rapidly optimise tracing functions f_k and g_k respectively. Both these schema involve central databases, the difference being that in one case the contact histories G_{ij} is pseudonymized, whilst in the other the contact histories are G_{ix} are anonymised with respect to one of the parties. Given that the point of decentralised systems is to enhance privacy, extensive data donation is likely not to be an allowed feature of such a system, and to date, no schemes have been developed for the evaluation and improvement of the function g_k.

Of the three schemas presented, the pure decentralised system clearly places higher value on the right to privacy than the right to life or the right to movement, which may seem acceptable only in the implicit but untested assumption that other privacy-preserving interventions exist to control the epidemic.

The decentralised model with data donation from only those individuals who are notified (schema 1) both constructs a central database and has poor convergence on good choices of function g_k , and so seems to have none of the benefits of any system.

Of the centralised system or the decentralised system with large data donation (schema 2), the centralised system has network information on fewer people, and less personal data stored on fewer phones. The benefits of anonymisation over pseudonymisation may be overstated when detailed contact histories are collected. Furthermore the centralised system allows tracing to proceed based on information from the source index case (time since symptom onset, severity of symptoms) which may plausibly predict infection risk better than using information from the recipient contact.

Precedent for the post-pandemic world

It is said that in a crisis, new norms are established which are hard to change. Democratic oversight of data use has functioned poorly in the recent past. There is a fear that surveillance to improve a pandemic response could lead to increased surveillance and coercive practices for future generations, and that increased data use for pandemic control could lead to increased data use for negative purposes. We propose that establishing the principle that governance should focus on a transparent process of balancing the right to privacy, the right to movement, and the right to life would be a step forwards in data governance.

The converse proposal, of prioritising the right to privacy over the right to life and the right to movement, only legitimises and reinforces the notion that digital solutions are not to be trusted to democratic oversight, and will be the exclusive purview of despots and autocrats, to all our detriment.

Conclusion

Digital contact tracing can contribute to the suppression of COVID-19 (maintaining $R<1$) whilst enabling more freedom of movement and economic activity than a lockdown. This is not a trivial task. The basic reproduction number of COVID is close to 3, and about half of transmissions occur before someone is symptomatic.

Success will depend on high uptake, trust in the beneficence of the system, that use of data and temporary loss of privacy has been commensurate with the task. It will also depend on engagement with the notifications issued by the app, and a widespread understanding that every effort has been taken to ensure that the system can realistically contribute to reducing transmission, and that the system that issues notifications is undergoing evaluation and improvement. Our aim here was to lay out some of the trade-offs in terms of these latter aims. Decentralised systems are a priori more privacy-preserving, and are currently supported by the operating system owners, which may enable larger uptake. Centralised systems may have a larger privacy cost, but for equal uptake, offer substantial benefits in terms of their intended potential public health benefits. Appropriate oversight of centralised systems may mitigate privacy risks.

Decisions taken at this stage will benefit from a clear understanding of the trade-offs between the three aims: preserving privacy, reducing infections, and minimising the number of people required to isolate.

The trade-offs could be reduced if a system emerges that combines benefits of each option and reduces drawbacks. At the present time, with sufficient oversight to ensure privacy is maintained in the centralised system, and if this oversight is transparent enough to encourage uptake, the centralised option will give more options to suppress COVID epidemic spread.

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Modeling the combined effect of digital exposure notification and non-pharmaceutical interventions on the COVID-19 epidemic in Washington state

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Abstract

Contact tracing is increasingly being used to combat COVID-19, and digital implementations are now being deployed, many of them based on Apple and Google's Exposure Notification System. These systems are new and are based on smartphone technology that has not traditionally been used for this purpose, presenting challenges in understanding possible outcomes. In this work, we use individual-based computational models to explore how digital exposure notifications can be used in conjunction with non-pharmaceutical interventions, such as traditional contact tracing and social distancing, to influence COVID-19 disease spread in a population. Specifically, we use a representative model of the household and occupational structure of three counties in the state of Washington together with a proposed digital exposure notifications deployment to quantify impacts under a range of scenarios of adoption, compliance, and mobility. In a model in which 15% of the population participated, we found that digital exposure notification systems could reduce infections and deaths by approximately 8% and 6%, effectively complementing traditional contact tracing. We believe this can serve as guidance to health authorities in Washington state and beyond on how exposure notification systems can complement traditional public health interventions to suppress the spread of COVID-19.

Introduction

The COVID-19 pandemic has brought about tremendous societal and economic consequences across the globe, and many areas remain deeply affected. Due to the urgency and severity of the crisis, the poorly understood long-term consequences of the virus, and the lack of certainty about which control measures will be effective, many approaches to stopping or slowing the virus are being explored.

In seeking solutions to this problem, many technology-based non-pharmaceutical interventions have been considered and deployed (*1*), including data aggregation to track the spread of the disease, GPS-enabled quarantine enforcement, AI-based clinical management, and many others.

Contact tracing, driven by interviews of infected persons to reveal their interactions with others, has been a staple of epidemiology and public health for the past two centuries (*2*). These human-driven methods have been brought to bear against COVID-19 since its emergence, with some success (*3*). Unfortunately, owing in part to the rapid and often asymptomatic spread of the virus, these efforts have not been successful in preventing a global pandemic. Further, as infections have reached into the millions, traditional contact tracing resources have been overwhelmed in many areas (*4*) (*5*). Given these major challenges for traditional contact tracing, technology-based improvements are being explored, with particular focus on the use of smartphones to detect exposures to others carrying the virus.

Smartphone apps may approximate pathogen exposure risk through the use of geolocation technologies such as GPS, and/or via proximity-based approaches using localized Radio Frequency (RF) transmissions like Bluetooth. Location-based approaches attempt to compare the places a user has been with a database of high-risk locations or overlaps with infected people (*6*), while proximity-based approaches directly detect nearby smartphones that can later be checked for "too close for too long" exposure to infected people (*7*). In either approach, users who are deemed to be at risk are then notified, and in some implementations, health authorities also receive this information for follow-up.

Due to accuracy and privacy concerns, the majority of contact tracing proposals have avoided the location signal and focused on a proximity-based approach, such as PEPP-PT (*8*) and NSHX (*9*). Further privacy safeguards may be achieved by decentralizing and anonymizing important elements of the system, as in DP-3T(*10*) and Apple and Google's Exposure Notifications System (ENS) (*11*). In these approaches, the recognition of each user's risk level can take place only on the user's smartphone, and server-side knowledge is limited to anonymous, randomized IDs.

Technological solutions in this space have never been deployed at scale before, and their effectiveness is unknown. There is an acute need to understand their potential impact, to establish and optimize their behavior as they are deployed, and to harmonize them with traditional contact tracing efforts. Specifically we will examine these issues in the context of ENS, which is currently being adopted by many countries (*12*).

There are many variables to consider when characterizing the behavior of any system of this type. Technology-dependent parameters, such as those needed to convert Bluetooth signal strength readings to proximity (*13*) (*14*), vary from device to device and require labor-intensive calibration. They will not be discussed in this paper. Here we seek to explore the general conditions and public health backdrop in which an ENS deployment may exist, and the policy characteristics that can accompany it.

In order to improve our understanding of this new approach, we employ individual-based computational models, also known as agent-based models, which allow the exploration of disease dynamics in the presence of complex human interactions, social networks, and interventions (*15*). This technique has been used to successfully model the spread of Ebola in Africa (*16*), malaria in Kenya (*17*), and influenza-like illness in several regions (*18*) (*19*), among many others. In the case of COVID-19, the OpenABM-Covid19 model by Hinch et a.l (*20*) has already been used to explore smartphone-based interventions in the United Kingdom. This model seeks to simulate individuals and their interactions in home, work, and community contexts, using epidemiological and demographic parameters as a guide.

In this work, we adapt the OpenABM-Covid19 model to simulate the ENS approach and apply it to data from Washington state in the United States in order to explore possible outcomes. We use data at the county level to match the population, demographic, and occupational structure of the region, and calibrate the model with epidemiological data from Washington state and Google’s Community Mobility Reports for a time-varying infection rate (*21*). Similar to Hinch et al., we find that digital exposure notification can effectively reduce infections, hospitalizations, and deaths from COVID-19 at all levels of participation. We extend the findings by Hinch et al. to show how digital exposure notification can be deployed concurrently with traditional contact tracing and social distancing to suppress the current epidemic and aid in various “reopening” scenarios. We believe the demographic and occupational realism of the model and its results have important implications for the public health of Washington state and other health authorities around the world working to combat COVID-19.

Methods

Modeling individual interactions and COVID-19 epidemiology

To model the combined effect of digital exposure notification and other non-pharmaceutical interventions (NPIs) in Washington state, we use a model first proposed by Hinch et al. (*20*), who have also made their code available as open source on GitHub (*22*). OpenABM-Covid19 is an individual-based model that models interactions of synthetic individuals in different types of networks based on the expected type of interaction (Fig. 1). Workplaces, schools, and social environments are modeled as Watts--Strogatz small-world networks (*23*), households are modeled as separate fully connected networks, and random interactions, such as those on public transportation, are modeled in a random network. The networks are parameterized such that the average number of interactions matches the age-stratified data in (*24*). Contacts between synthetic individuals in those interaction networks have the potential for transmission of the virus that causes COVID-19 and are later recalled for contact tracing and possible quarantine.

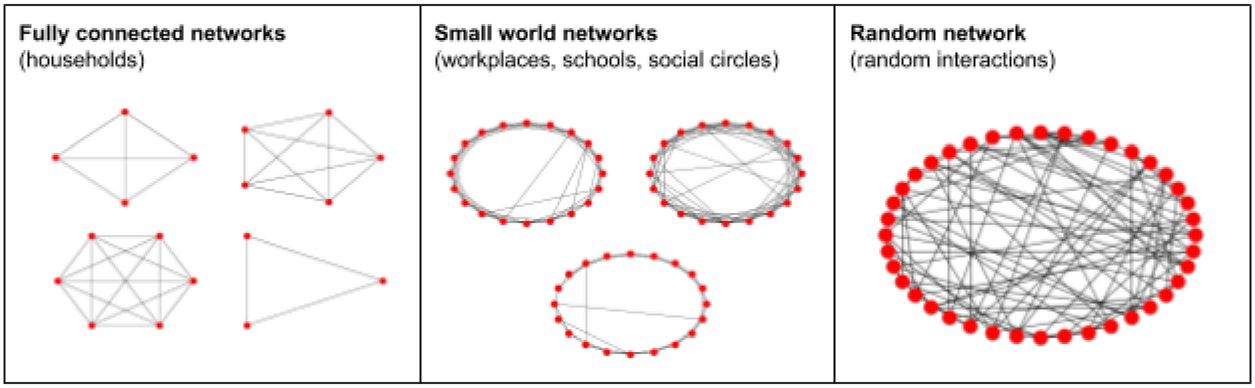


Fig. 1. Examples of fully connected, Watts–Strogatz small-world, and random networks that define interactions among synthetic agents in households, workplaces, schools, social circles, and random settings.

While the original model by Hinch et al. (*22*) included a single occupation network for working adults, we extend this to support multiple networks for workplace heterogeneity. This is motivated by increasing evidence that workplace characteristics play an important role in the spread of SARS-CoV-2, such as having to work in close physical proximity to other coworkers and interacting with the public. Baker et al. found that certain U.S. working sectors experience a high rate of SARS-CoV-2 exposure, including healthcare workers, protective services (e.g., police officers), personal care and services (e.g., child care workers), community and social services (e.g., probation officers) (*25*). As another example, the Centers for Disease Control and Prevention (CDC) has issued specific guidance to meat and poultry processing workers due to the possible increased exposure risk in those environments (*26*). Therefore, we model each individual industry sector as its own small-world network and parameterize it with real-world data such as the sector size and interaction rates.

In OpenABM-Covid19, transmission between infected and susceptible individuals through a contact is determined by several factors, including the duration since infection, susceptibility of the recipient (a function of age), and the type of network where it occurred (home networks assume a higher risk of transmission due to the longer duration and close proximity of the exposure). Individuals progress through stages of susceptible, infected, recovered, or deceased. In this model, the dynamics of progression through these stages are governed by several epidemiological parameters, such as the incubation period, disease severity by age, asymptomatic rate, and hospitalization rate, and are based on the current literature of COVID-19 epidemiology. A complete list of the epidemiological parameters can be found at (*27*) and any modifications to those are described in the subsequent sections and documented in the supplementary materials (Table S1, S2).

Modeling Washington state

In this work we model the three largest counties in Washington state -- King, Pierce, and Snohomish -- with separate and representative synthetic populations. The demographic and household structure were based on data from the 2010 U.S. Census of Population and Housing (*28*) and the 2012-2016 ACS Public Use Microdata Sample (*29*). We combined Census and Public Use Microdata Sample (PUMS) data using a method inspired by (*30*). For each Census block in Washington state we took distributions over age, sex, and housing type from several marginal tables (called Census Summary tables) and from the PUMS, and combined them into a multiway table using the iterative proportional fitting (IPF) algorithm. We then resampled the households from the PUMS to match the probabilities in the multiway table. The resulting synthetic population in each Census block respects the household structure given by PUMS and matches marginals from the Census Summary tables.

Our synthetic working population was drawn to match the county-level industry sector statistics reported by the U.S. Bureau of Labor Statistics in their Quarterly Census of Employment and Wages for the fourth quarter of 2019 (*31*). We also used a report by the Washington State Department of Health (DOH) containing the employment information of lab-confirmed COVID-19 cases among Washington residents as of May 27, 2020 to parameterize each occupation sector network (*32*). For each sector, we use its lab-confirmed case number weighted by the total employment size as a multiplier factor to adjust the number of work interactions of that occupational network. While the DOH report does not explicitly measure exposure risk for different industries, it is, to the best of our knowledge, the best source of data for confirmed COVID-19 cases and occupations to date. Our model should be refined with better data from future work that studies the causal effect of workplace characteristics on COVID-19 transmission. A complete list of the occupation sectors and interaction multipliers can be found in the supplementary materials (Table S3,S4).

Modeling interventions

Testing and quarantine

In the OpenABM-Covid19 model, if an individual presents with COVID-19 symptoms, they receive a test and are 80% likely to enter a voluntary 7-day isolation with a 2% drop out rate each day for noncompliance. If the individual receives a positive test result, they isolate for a full 14 days from initial exposure with a daily drop out rate of 1%. Prior to confirmation of the COVID-19 case via a test result, the household members of the voluntarily self-isolating symptomatic individual do not isolate, which is in line with current recommendations by the CDC (*33*). Household quarantines may still occur through digital exposure notification or manual contact tracing, described in the following sections.

Digital exposure notification

We simulate digital exposure notification in OpenABM-Covid19 by broadcasting exposure notifications to other users as soon as an app user either tests positive or is clinically diagnosed with COVID-19 during hospitalization. The model recalls the interaction networks of this app user, known as the “index case”, to determine their first-order contacts within the previous 10 days. Those notified contacts are then 90% likely to begin a quarantine until 14 days from initial exposure with a 2% drop out rate each day for noncompliance. See (*22*) for a more comprehensive description of the model.

While the actual ENS allows health authorities to configure notifications as a function of exposure distance and duration, our model does not have the required level of resolution and instead assumes that 80% of all “too close for too long” interactions are captured between users that have the app. (See the supplemental materials for a sensitivity analysis of this parameter.)

The overall effect of digital exposure notification depends on a number of factors that we explore in this work, including the fraction of the population that adopts the app and the delay between infection and exposure notification. As an upper bound on app adoption, we configure the age-stratified smartphone population using data on smartphone ownership from the U.S. from the Pew Research Center (*34*) for ages 20+ and Common Sense Media (*35*) for ages 0-19. Since this data was not available for Washington state specifically we assumed that the U.S. distribution was representative of Washington state residents.

Manual contact tracing

We also extend OpenABM-Covid19 to model traditional or “manual” contact tracing as a separate intervention. In contrast to digital exposure notification, human tracers work directly with index cases to recall their contact history without the proximity detection capabilities of a digital app. Those contacts are then given the same quarantine instructions as those traced through the digital app. We configure the simulation such that manual contact tracers have a higher likelihood of tracing contacts in the household and workplace/school networks (100% and 80%, respectively) than for the additional random daily contacts (5%). This is based on the assumption that people will have better memory and ability to identify contacts in the former (e.g., involving family members or coworkers) compared to the latter (e.g., a random contact at a restaurant). Additionally, we configure the capacity of the contact tracing workforce with parameters for workforce size, maximum number of index-case interviews per day, and maximum number of tracing notification calls per day following those interviews. Tracing is initiated on an index case after either a positive test or hospitalization, subject to the capacity in that area. Finally, we add a delay parameter between initiation of manual tracing and finally contacting the traced individuals to account for the processing and interview time of manual tracing.

Model calibration

Model calibration is the process of adjusting selected model parameters such that the model's outputs closely match real-world epidemiological data. To calibrate OpenABM-Covid19 for Washington state we use components of a Bayesian SEIR model by Liu et al. (*36*) for modeling COVID-19. They extend the classic SEIR model by allowing the infection rate to vary as a function of human mobility and a latent changepoint to account for unobserved changes in human behavior. We fit that model to Washington state county-level mortality data from *The New York Times (37)* and mobility data from the Community Mobility Reports published by Google and publicly available at (*21*). The Community Mobility Reports are created with aggregated, anonymized sets of data from users who have turned on the Location History setting, which is off by default. No personally identifiable information, such as an individual's location, contacts or movement, is ever made available (*38*). The reports chart movement trends over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. We note that, because of the opt-in nature of this dataset, it may not be representative of the overall population.

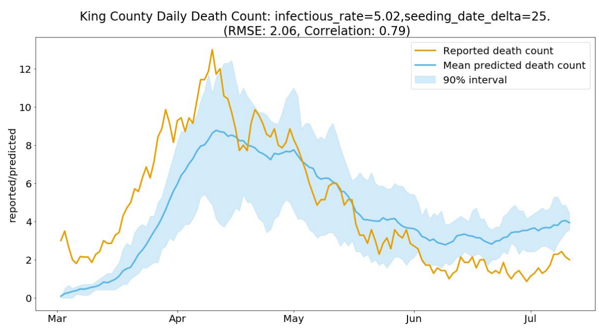
We extend the methodology in Liu et al. to model calibration in OpenABM-Covid19 by applying the time-varying infection rate coefficients to the relevant county-specific parameters that guide user interaction levels and disease transmission likelihood. More specifically, the number of daily interactions in the random and occupation networks, $Ri(t)$ and $Wi(t)$, are scaled by the mobility coefficient, $m(t)$ at time step t, which is calculated based on the aggregated and anonymized location visits from the Community Mobility Reports. The time-dependent infectious rate, $\beta(t)$, is scaled by a weighting term, $\sigma(t)$, that depends on how far time step t is from a learned changepoint, which is modeled as a negative sigmoid. Both $\sigma(t)$ and $m(t)$ are learned functions and are described in more detail in (*36*).

Finally, we use an exhaustive grid search to compute two OpenABM-Covid19 parameters for each county: its initial infectious rate and the infection seed date[1]. The infectious rate is the mean number of individuals infected by each infectious individual with moderate-to-severe symptoms, and can be considered a function of population density and social mixing. The infection seed date is the date at which the county reaches 30 total infections, possibly before the first official cases due to asymptomatic and unreported cases. We pick the parameters where the simulated mortality best matches the actual COVID-19 mortality from epidemiological data, as measured by root-mean-square error (RMSE).

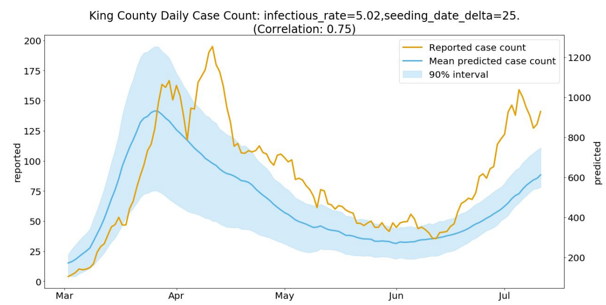
The results of the calibrated models for King, Pierce, and Snohomish counties are shown in Fig. 2. Note that while there is a strong correlation in the predicted and reported incidence, the

[1] We exhaustively searched from 3.0-7.0 for the infectious rate parameter and 35 day period for the infection seed date.

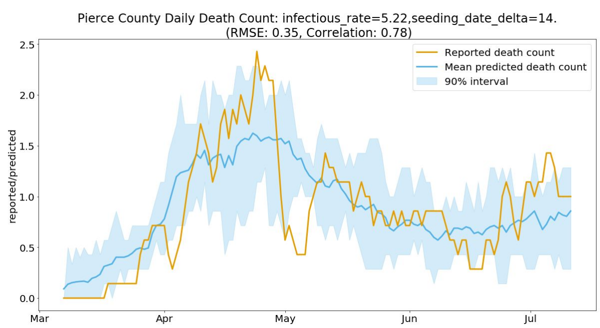
absolute predicted counts are approximately 6X higher than those that were officially reported. We attribute this difference to the fact that OpenABM-Covid19 is counting all asymptomatic and mild symptomatic cases that may not be recorded in reality. This is approximately consistent with the results of a seroprevalence study by the CDC that estimated that there were 6 to 24 times more infections than official case report data (*39*).



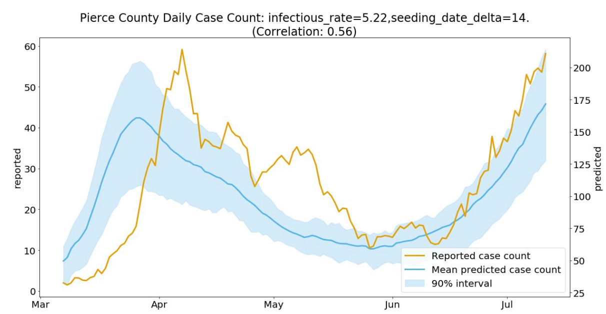
(A) RMSE: 2.06, Correlation: 0.79



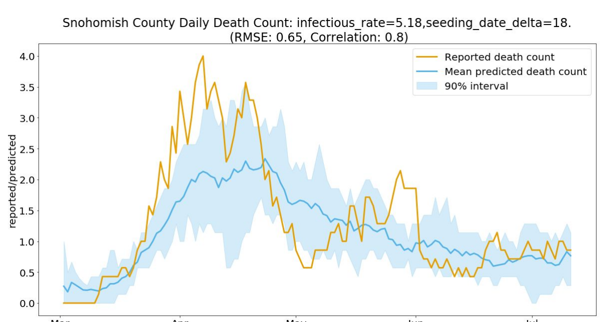
(B) Correlation: 0.75



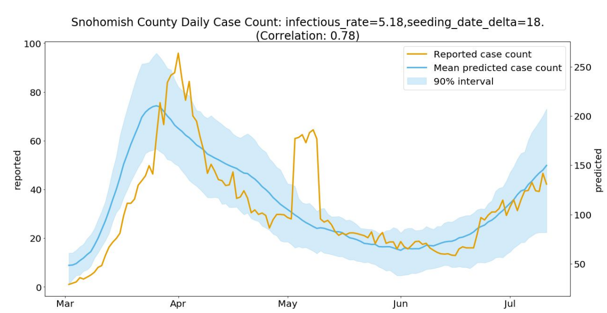
(C) RMSE: 0.35, Correlation: 0.78



(D) Correlation: 0.56



(E) RMSE: 0.65, Correlation: 0.80



(F) Correlation: 0.78

Fig. 2. Daily reported and predicted COVID-19 deaths in King County, WA (A), Pierce County, WA (C), and Snohomish County, WA (E) and daily reported and predicted COVID-19 cases for King County, WA (B), Pierce County, WA (D), and Snohomish County, WA (F).

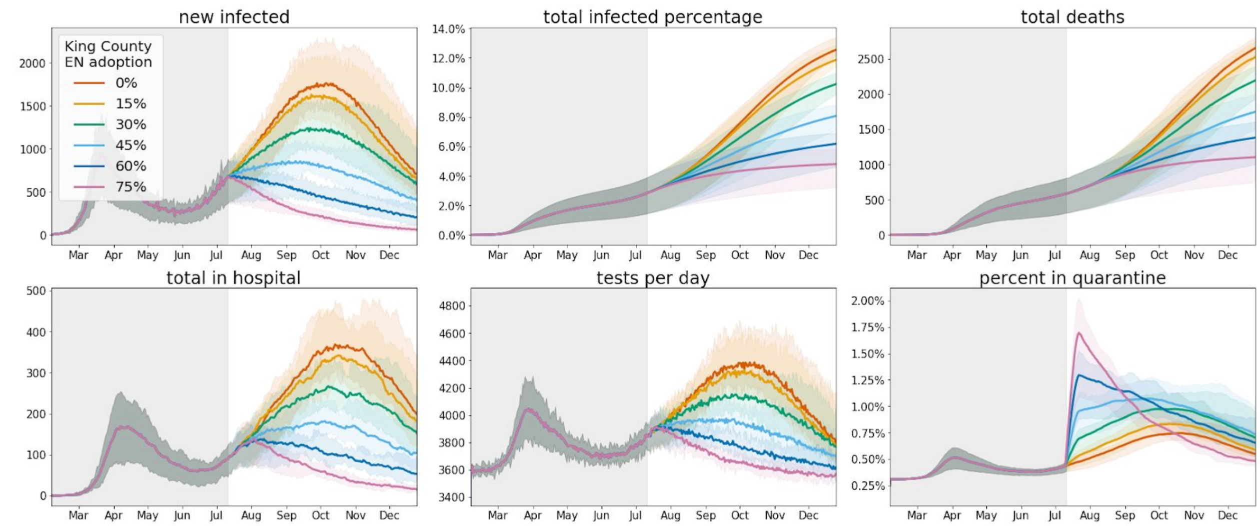
Results

In this section we present several forward-looking simulations for Washington state counties by comparing multiple hypothetical scenarios that implement some combination of digital exposure notification, manual contact tracing, or social distancing. Each simulation uses the same calibrated model parameters up to July 11, 2020 at which point the hypothetical interventions are implemented. Beyond this date, each simulation uses the model parameters from the last week of the calibration period, except where explicitly specified as part of the intervention. For each simulated intervention we report the number of infections (daily and cumulative), cumulative number of deaths, number of hospitalizations, number of tests per day, and fraction of the population in quarantine. Each simulation covers 300 consecutive days from March 1, 2020 through Dec 25, 2020, plus the additional calibrated seeding period before March 1. Unless otherwise stated, the reported result is the mean value over 10 runs with different random seeds of infection.

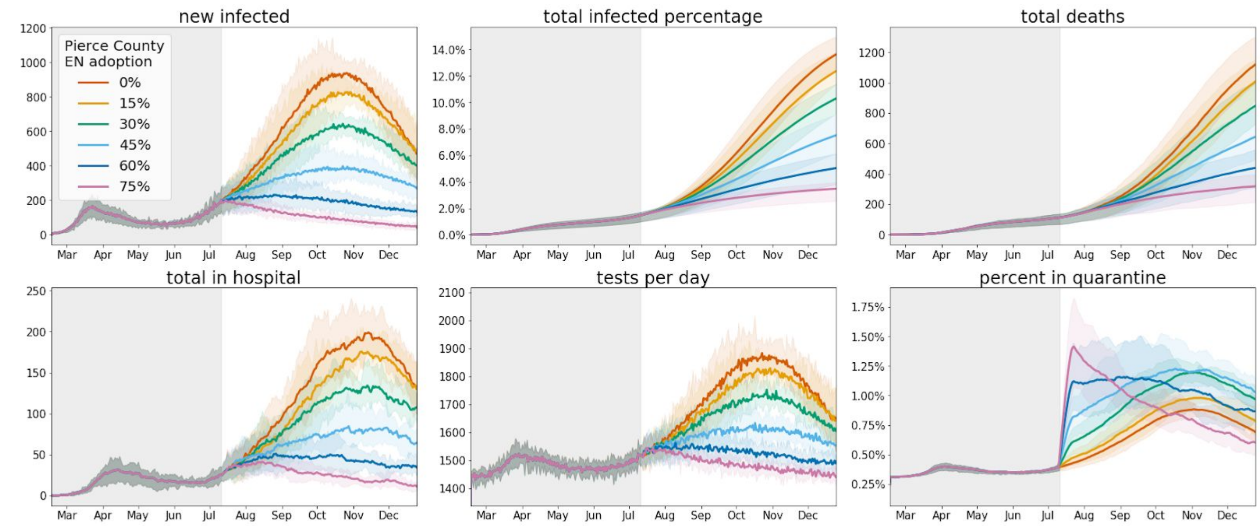
Note that results may be affected by the end date of the simulation because of the time it takes some interventions to have their full effect. We believe that a time horizon of approximately 5 and a half months is long enough to be practically useful for public health agencies who are considering deploying such interventions, but short enough to minimize the long-term uncertainty and effects of externalities such as a vaccine becoming available.

Digital exposure notification

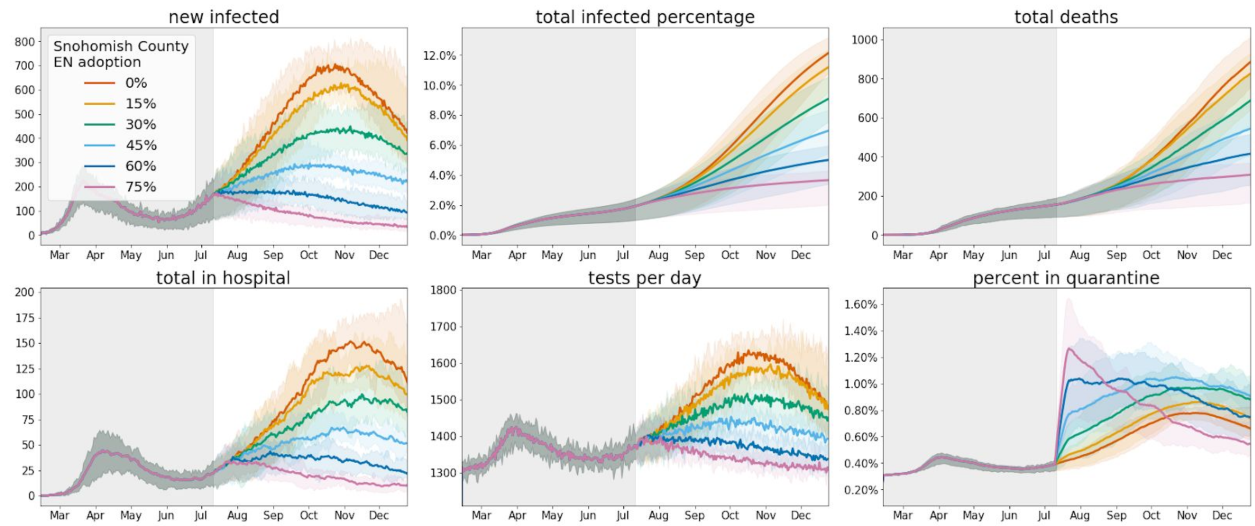
We first study the effect of a digital exposure notification app at different levels of app adoption -- 15%, 30%, 45%, 60%, and 75% (or all smartphone owners) -- of the population in each county. As a baseline, we compare those results to the “default” scenario without digital exposure notification and assume no change in behavior or interventions beyond July 11, 2020. The results show an overall benefit of digital exposure notification at every level of app adoption (Fig. 3 and 4). When compared to the default scenario of only self isolation due to symptoms, each scenario results in lower overall incidence, mortality, and hospitalizations. Unsurprisingly, the effect on the epidemic is more significant at higher levels of app adoption. An app with 75% adoption reduces the total number of infections by 56-73%, 73-79%, and 67-81% and the number of total deaths by 52-70%, 69-78%, and 63-78% for King, Pierce, and Snohomish counties, respectively. Even at a relatively low level of adoption of 15%, total infections are reduced by 3.9-5.8%, 8.1-9.6%, and 6.3-11.8% and total deaths are reduced by 2.2-6.6%, 11.2-11.3%, and 8.2-15.0% for King, Pierce, and Snohomish counties, respectively.



(A) King County, WA



(B) Pierce County, WA



(C) Snohomish County, WA

Fig. 3. Simulation results for various levels of exposure notification app uptake (among the total population) during 2020, with the app being implemented on July 11, 2020 in (A) King, (B) Pierce, and (C) Snohomish counties. The shaded areas represent the 97.5% confidence intervals.

King Pierce Snohomish

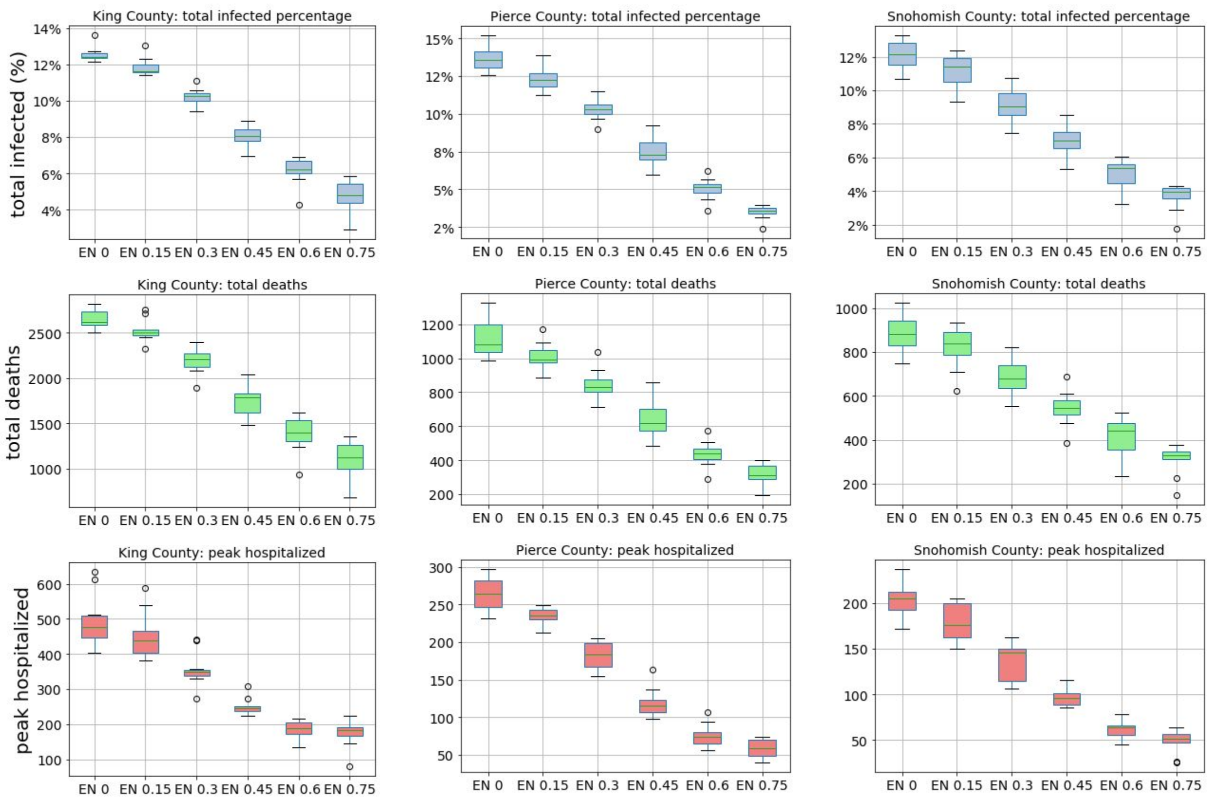


*Fig. 4. Estimated total infected percentage, total deaths, and peak in hospital (y-axes) of King, Pierce, and Snohomish counties for various levels of exposure notification (EN) app uptake among the population (x-axis) between July 11, 2020 and December 25, 2020. The boxes represent the Q1 to Q3 quartile values with a line at the median. The whiskers show the range of the data (1.5 * (Q3-Q1)) and any outlier points are past the end of the whiskers.*

In addition to its effect on the epidemic, we also evaluate the trade-off between exposure notification app adoption and the total number of quarantine events. There is an incentive to minimize the quarantine rate because of the perceived economic and social consequences of stay-at-home orders. At 15% exposure notification app adoption the number of total quarantine events increases by 4.6-6.4%, 6.6-6.8%, and 5.8-10.2% for King, Pierce, and Snohomish counties (Fig. 5). In general, the higher the level of exposure notification adoption the greater the number of total quarantine events, with the exception of very high levels of adoption (60% and 75%) where this number plateaus or even decreases, likely due to the significant effect of the intervention in suppressing the overall epidemic in those scenarios. From another perspective, achieving epidemic control at the price of high initial quarantine is preferable to lower levels of quarantine that are sustained for much longer.

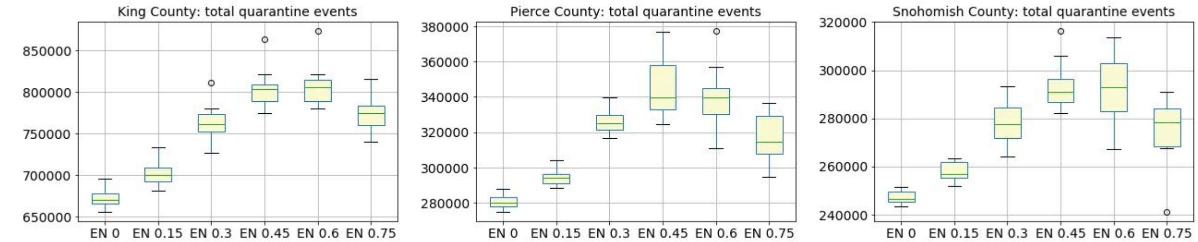


Fig. 5: Estimated total quarantine events of King, Pierce, and Snohomish counties for various levels of exposure notification app uptake among the population from July 11, 2020 to December 25, 2020. Note that even for the "default" (0% EN app uptake) scenario there is a non-zero number of quarantine events because this assumes that symptomatic and confirmed COVID-19 positive individuals will self-quarantine at a rate of 80%, even in the absence of an app.

Manual contact tracing

Next we study the potential impact of manual contact tracing in suppressing the epidemic as a function of the contact tracing workforce size. We refer to the Office of the Governor of WA State that recommends, at minimum, 15 tracers per 100,000 people. Furthermore we use the current staffing rates for King County including all available staffers (105 full-time workers for 2.253 million people, or 4.7 per 100,000) (*40*) and the National Association of County & City Health Officials (NACCHO) recommended staffing levels during epidemics of 30 tracers per 100,000 people (*41*). We set the tracing delay to one day to be consistent with Washington state's goal of notifying 80% of contacts within 48 hours (*42*), and use the King County Phase 2 Application to compute the expected rate of initial contact tracing interviews and follow-up notifications. Over a two-week period, 22 staff members contacted 336 individuals for initial interviews and 941 for close contact notifications, or approximately 1 initial interview and 3 notifications per day per staff member (*40*).

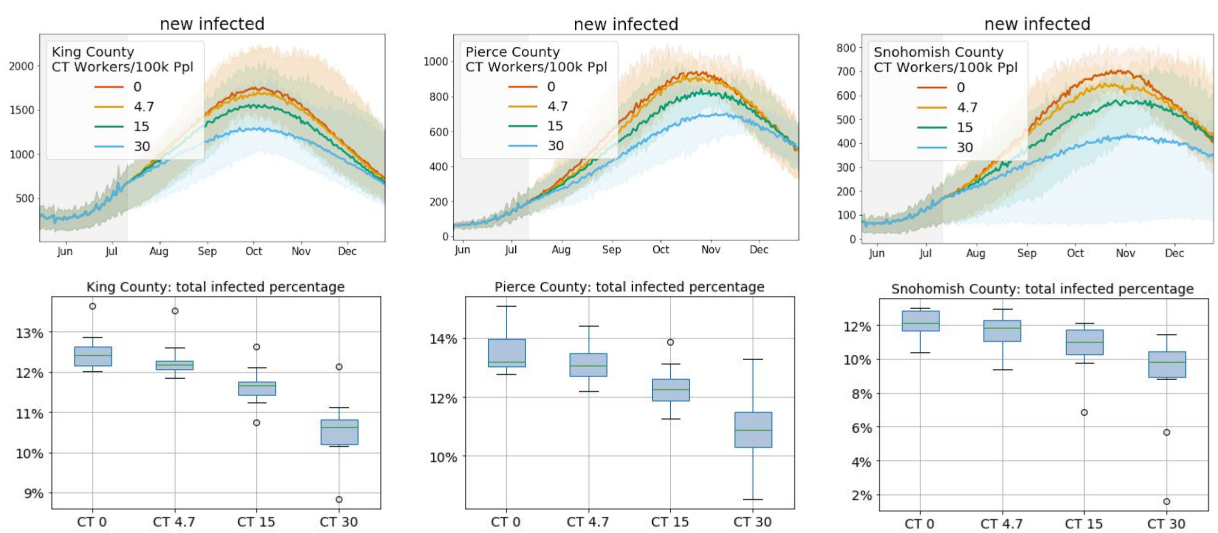


Fig. 6. Estimated effect of manual contact tracing on new infections (top) and total infected percentage (bottom) at various staffing levels per 100k people in King, Pierce, and Snohomish counties between July 11, 2020 and December 25, 2020.

Manual tracing with the full desired staffing levels of 15 workers per 100,000 people is able to affect the epidemic trend in all three counties, but has a significantly smaller effect at current staffing levels (Fig. 6). Unsurprisingly, the impact for a given level of staffing is dependent upon the current epidemic trend, reinforcing the need for concurrent interventions to effectively manage the epidemic.

Additionally, we compare the performance of exposure notification to manual contact tracing to establish similarities between relative staffing level and exposure notification adoption and to verify an additive effect of concurrent manual tracing and exposure notification.

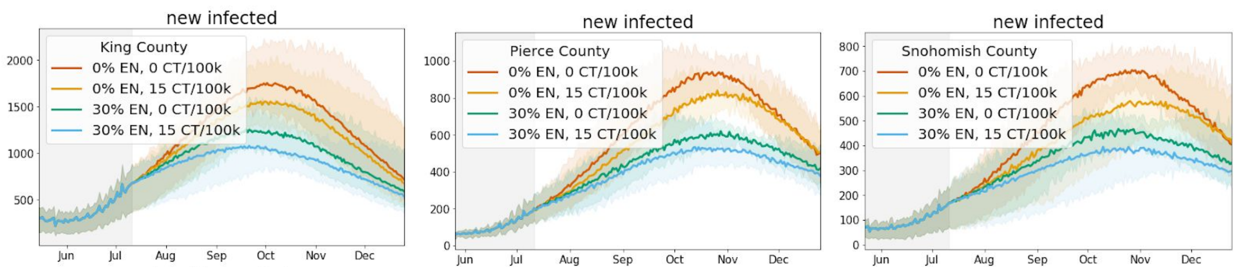


Fig. 7. Comparison between manual contact tracing (CT) at the recommended staffing level and exposure notification (EN) at 30% adoption in King, Pierce, and Snohomish counties.

We see improvements in all cases when combining interventions (Fig. 7). In all three counties, exposure notification has a stronger effect at the given staffing and adoption levels, but adding either intervention to the other results in reduced infections, albeit to different extents based on the trend of the epidemic. This suggests that both methods are useful separately and combined, even if they do not explicitly coordinate.

Concurrent interventions under behavioral changes

While the results shown above suggest that the interventions are effective in suppressing the COVID-19 epidemic to various degrees, in practice, health organizations will implement multiple intervention strategies simultaneously to try to curb the spread of the virus while also allowing controlled reopenings. Therefore, we also study the combined effect of concurrent interventions including digital exposure notification, manual contact tracing, and social distancing (Fig. 8). We model social distancing as a function of infectiousness of interactions in the random and occupation networks, where increasing social distancing decreases the relative transmission likelihood on a network by a multiplicative factor relative to their values as of March 1, 2020 (i.e., before broad-based social distancing and mobility reductions). For example, social distancing of 1.7x is equivalent to multiplying the relative transmission by 1 / 1.7 = 0.6. Note that this does not change the number of person-to-person interactions, but rather the likelihood of transmission of any individual encounter, which may be affected by factors other than physical distancing such as mask usage, improved hygiene, use of personal protective equipment, etc.

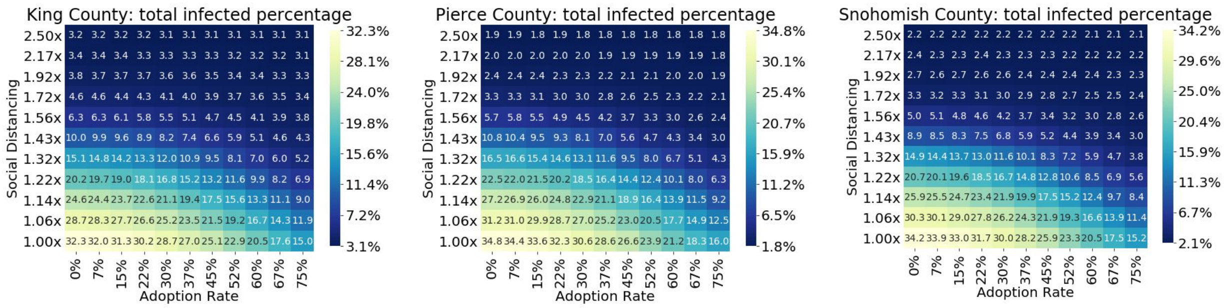


Fig. 8. Estimated total infected percentages between July 11 to December 25, 2020 for King, Pierce, and Snohomish counties as a function of simultaneous social distancing and exposure notification app adoption. Social distancing is expressed as the infectiousness of random and occupation network interactions, relative to their initial values (i.e., before broad-based social distancing and mobility reductions).

Next we examine the effects of combined NPIs under various "reopening" scenarios by gradually increasing the number of interactions in every interaction network, including households, workplaces, schools, and random networks. Specifically, we increase these interactions by a given percentage from the levels as of July 11, 2020 (0% reopen) up to the initial levels at March 1, 2020, at the very start of the epidemic (100% reopen). Given the average number of interactions i for network n at the end of the baseline as $i_{b,n}$ and before the lockdown as $i_{0,n}$, the network reopening percentage p (in 0-100%) defines the current relative interactions under reopening $i_{c,n}$ as

$$i_{c,n} = \frac{p}{100}(1 - i_{b,n}) + i_{b,n} .$$

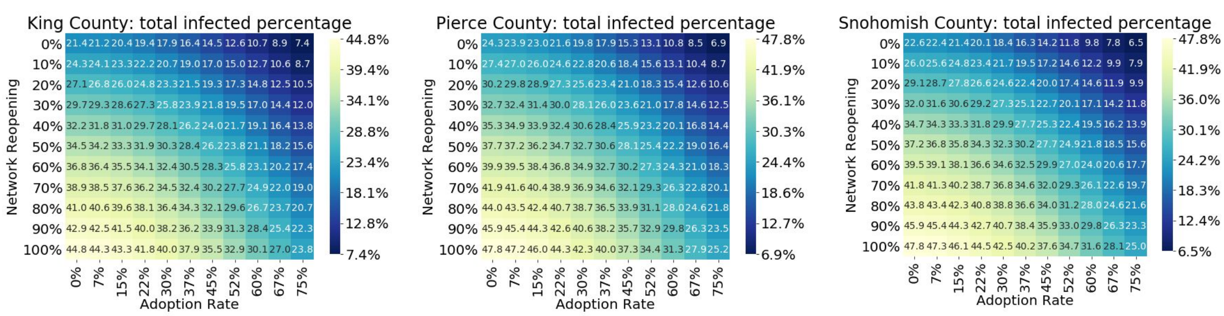


Fig. 9. Estimated total infected percentage as a function of simultaneous network reopening and exposure notification app adoption rates, assuming fully staffed manual contact tracing (15 workers per 100,000 people).

The increase in new infections from a 10-20% reopening are balanced by 22-37% exposure notification app adoption, although the effect varies by county (Fig. 9). This shows that limited additional reopenings may be possible after introducing exposure notification alongside existing fully staffed manual tracing (15 staff per 100,000 people), but that social distancing remains an important measure under these circumstances. Additionally, there is an increased effect to adding exposure notification under greater reopening scenarios. As an example, we plot some primary metrics for a 50% network reopening and see significant reductions in nearly all metrics at even 30% adoption (Fig. 10).

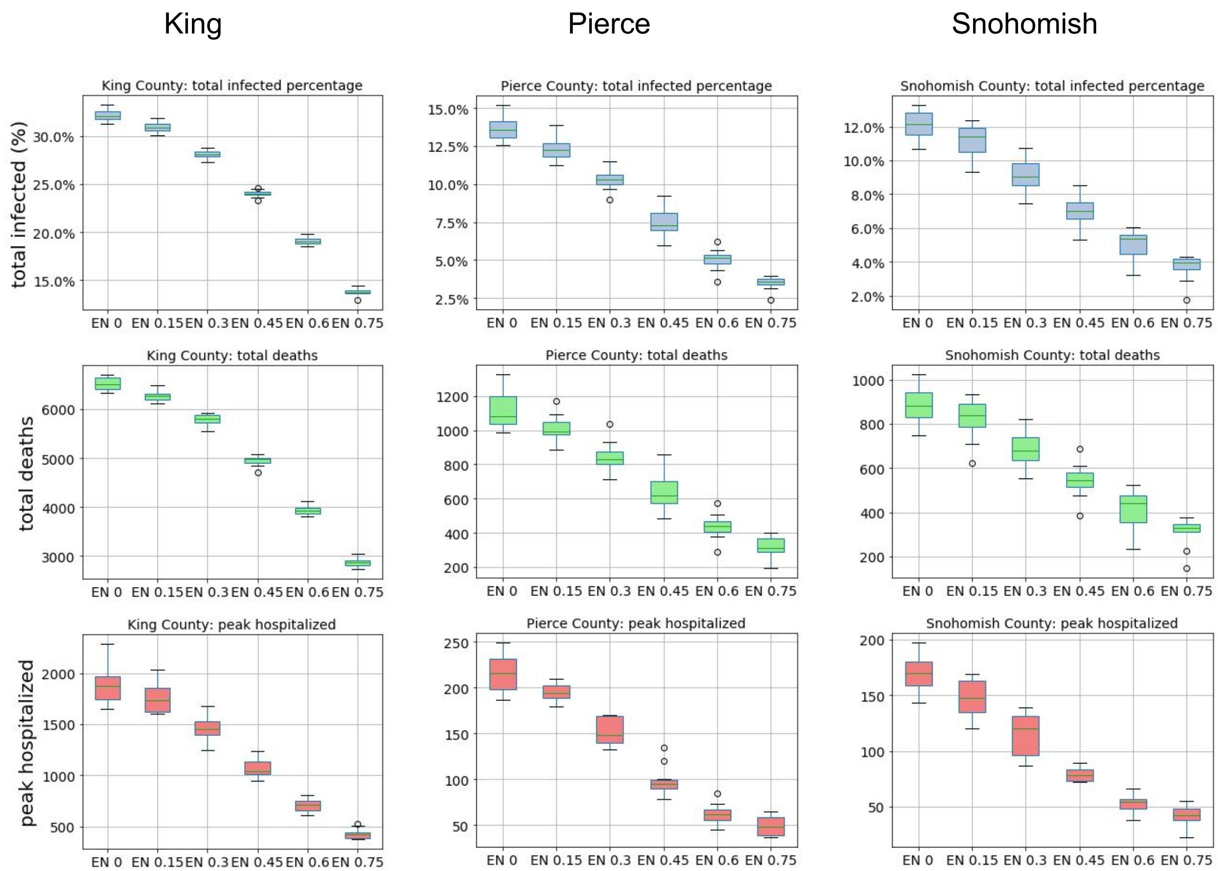


Fig. 10. Estimated total infected percentage, total deaths, and peak hospitalized under a 50% reopening scenario (an increase of 50% of the difference between pre-lockdown and post-lockdown network interactions) at various exposure notification adoption rates for King, Pierce, and Snohomish Counties, assuming no change to social distancing $\beta(t)$ *after the baseline and 15 manual contact tracers per 100k people.*

As part of the Washington State Department of Health's "Safe Start" plan, a key target metric to reopen Washington is to reach fewer than 25 new cases per 100,000 inhabitants over the prior two weeks (*42*). Here, we examine how many days it would take to reach that target under the combined NPIs. With the recent spike in cases, the trajectory for reaching these targets without renewed lockdowns is out of the range of the simulations. Therefore, to show the relative benefits of the NPIs, we introduce an artificial renewed lockdown at the mobility levels averaged over the month before the Phase 2 reopenings (Phase 1.5 for King County) that occurred on June 5, 2020. Using this averaged mobility from May 6 to June 5, 2020, we model the relative effects of manual tracing and exposure notification on the Washington Safe Start key metric.

We find that for all three counties, manual contact tracing at the recommended staffing levels combined with an exposure notification app can significantly reduce the amount of time it takes to achieve this metric (Fig. 11). Under the recommended standard for manual tracing, adding exposure notification at 30% adoption results in reaching the target in 92%, 87%, and 85% of the time versus no exposure notification for King, Pierce, and Snohomish counties respectively. At the reduced levels of 4.7 tracers per 100,000 population, the target is reached in less than 83% and 88% of the time for King and Snohomish respectively, although the exact ratio can not be calculated as the metric is not achieved in the baseline simulation.

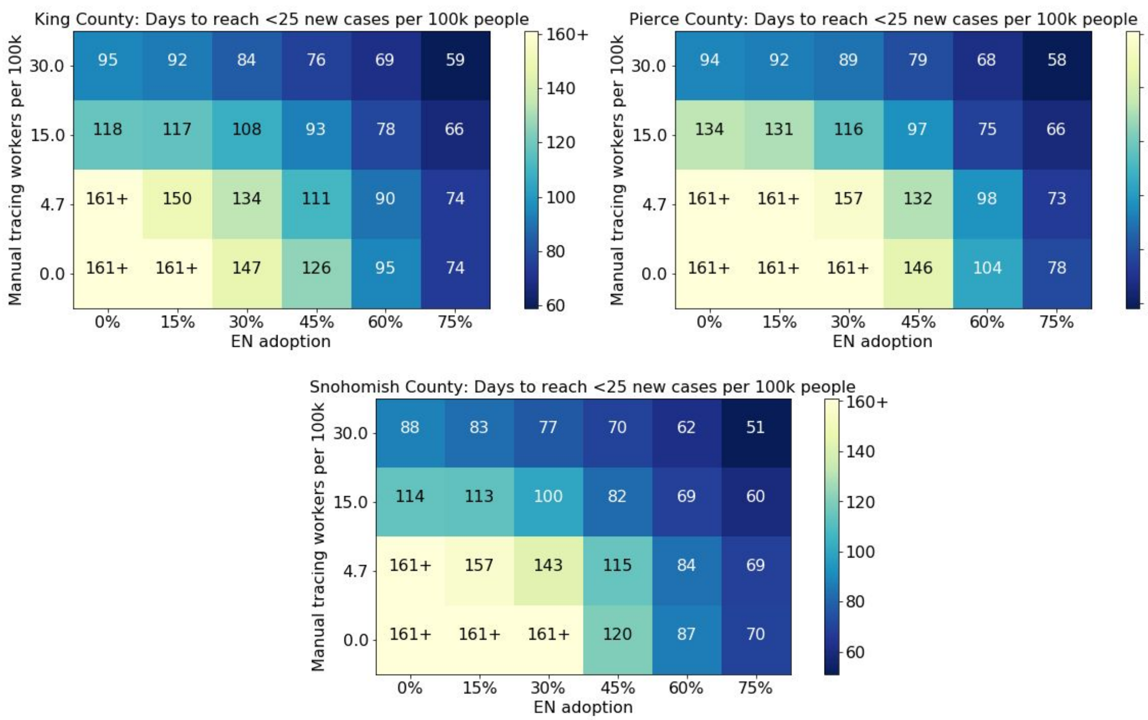


Fig. 11. Estimated number of days from July 11, 2020 for King, Pierce, and Snohomish counties to reach the Washington state goal of fewer than 25 new cases per 100,000 people over the trailing 14 days, as a function of manual tracing workforce capacity and exposure notification app adoption, given a renewed lockdown to the average level over the month before June 5th.

Limitations and Assumptions

Our individual-based modeling approach attempts to simulate the behavior of humans in a complex environment, in order to better understand the relative effects of different levels of intervention. While we have attempted to add realistic elements and calibrate it with the best available data, it still represents a dramatic simplification of the real world. Choices and simplifications made surrounding the behavior of the individuals, their movements in the world, disease dynamics, and many others, mean that the results should be viewed as an exploration of possible outcomes, not a prediction (*43*).

A more specific limitation in our work is that we modeled each county separately without cross-county interactions. In particular, we did not model how cross-county human movement contributes to disease spreading. We plan to explore this effect in our future work.

Our simulations assume that it takes 2 days from symptom onset to receive a COVID-19 test result and we acknowledge that this is a key assumption underlying our findings. Ferretti et al. (*44*) showed that the delay between the initial exposure to case confirmation, notification, and quarantine has a significant impact on the efficacy of the intervention. Rapid testing protocols can shorten the time between symptom development and case confirmation, and are essential for epidemic control (*20*).

We used published COVID-19 mortality data to calibrate model parameters. While the death count is arguably a good proxy to the true infection numbers, the published mortality data are scarce and noisy in small counties, resulting in the difficulty of modeling those counties with accuracy.

The synthetic occupation networks are based on the latest employment data corresponding to the fourth quarter in 2019 (*31*). Since the beginning of the pandemic, the size and structure of occupation networks may have changed compared to the latest available data.

In our work we used the mobility data along with a changepoint to model time-varying infection rates. While the changepoint vector models the net effect of various latent factors, it may be limited when multiple change points or more complex latent factors exist. The derived time-varying infection rate is homogeneously distributed to the random network and occupational networks. This is an approximation to the reality where the change may vary on different networks.

Related Work

The compartmental modeling approach (*45*) (*46*) (*47*) has been widely used for epidemic study. This approach segments the total population by subgroups according to the disease progression stage and models the transmission of stages with differential equations. SEIR (susceptible-exposed-infected-recovered) (*48*) (*49*) (*50*) (*44*) is a common type of compartmental model used to study COVID-19 spread. However, this approach is not suitable for studying the impact of individual level interventions like exposure notification apps because they characterize the disease dynamics at a population-level.

In contrast to the compartmental model, the individual-based modeling approach (*13*, *18*, *19*, *51*–*62*) simulates the infectious disease progression of individuals and can consider demographics, social interactions, and the environment. These individual-based models can predict the spread of COVID-19 in multiple countries by fitting the stochastic model of disease progression and human interactions from historical data. However, the impact of additional interventions such as digital exposure notification is unexplored.

In (*63*) (*64*), disease transmission is modeled by a stochastic process to fit the reproduction number of the total population. However, manipulating the reproduction number by real contact tracing actions can be challenging as it is subject to human interaction patterns, adoption rate, and many other types of interventions. This model lacks the characteristics of individuals as it uses the mean field theory to approximate the total population. (*65*) (*66*) (*67*) study contact tracing by situating individuals randomly in a space and mimicking human contacts by the individual's collision from the spatial movement. While this spatial individual-based model reveals promising results in virus spread in relatively small and closed areas, such as public buildings (*68*), and cruise ships (*69*), the ad-hoc assumptions in individual mobility patterns are not suitable for studying the impact of contact tracing in the scale of a city. (*70*) introduces the spatial temporal model which has more realistic mobility patterns. However, the spatial movement used in these models is a simplification of contact tracing which lacks the individual interactions among family members, workmates and from random activities. The effectiveness of manual and digital contact tracing is discussed in (*71*) through empirical contact data collected from the work related network at a small scale, without considering virus spread among family members and other random interactions. The references (*57*) (*72*) are the closest to ours, but they do not cover the joint impact of manual and digital contact tracing. In addition, model calibration is missing in their case studies. In contrast, OpenABM-Covid19 (*22*) simulates concurrent manual contact tracing and digital exposure notification interventions over interaction networks at a large scale.

Discussion

In this study we conducted a model-based estimation of the potential impact of a digital exposure notification app in Washington state. OpenABM-Covid19 simulates interactions among synthetic agents in various small-world networks, representing households, workplaces, schools, and random interactions. Interactions in those networks can result in COVID-19 transmission and are recalled to simulate different tracing interventions, including "manual" contact tracing or digital exposure notification, such as the recently released Apple and Google Exposure Notifications System (ENS). We calibrated our model using real-world data on human mobility and showed how it can accurately match epidemiological data in Washington state's three largest counties, King, Pierce, and Snohomish.

Similar to Hinch et al.'s report on digital contact tracing in the UK (*20*), we found that a digital exposure notification app can meaningfully reduce infections, deaths, and hospitalizations in these Washington state counties at all levels of app uptake, even if only a small fraction of the eligible population participates. We also showed how digital exposure notification can be combined with manual contact tracing at the recommended levels to further suppress the epidemic, even if the two interventions do not explicitly coordinate. Our simulations showed that the simultaneous deployment of both interventions can help these Washington counties meet the key incidence metric defined by the Safe Start Washington plan before December, 2020. The potential overall effect of digital exposure notification seems to be greater than even optimal levels of manual contact tracing, likely because of its ability to scale and better identify random interactions.

We also found that quarantine rates, which contribute to the social and economic cost of these interventions, scale sublinearly with app adoption, meaning that in some cases there are fewer people quarantined even though a greater fraction of the population is participating in the app. We credit this effect to the success of the app at suppressing the epidemic at high levels of adoption. Given a longer simulation time horizon we may see a similar effect even at the lower levels of app adoption. Health authorities may consider this when appealing to the public by explaining how greater rates of collective participation may reduce the severity of the epidemic while also minimizing or reducing the need for quarantine.

Finally, we looked at the combined effects of digital exposure notification and manual tracing in the context of different reopening scenarios, where mobility and interaction levels increase to the pre-epidemic levels. Our results suggest that both interventions are helpful in counterbalancing the effect of reopening, but are not totally sufficient to offset new cases except at very high levels of adoption and manual tracing staffing. As a result we believe that continued social distancing and limiting person-to-person interactions is essential. Future work is needed to study targeted reopening strategies, such as reopening specific occupation sectors or schools, or more stringent social distancing interventions in places that do reopen.

Looking ahead to future work, we are considering the question of coordination between different regions when deploying digital exposure notification as part of a suite of non-pharmaceutical interventions. The United States has seen a highly spatially varied response to the COVID-19 pandemic, with significant consequences to epidemic control (*73*). Under the conditions of varying cross-county and cross-state flows, we seek to quantify the empirical efficiency gap between coordinated and uncoordinated deployments and policies around testing, tracing, and isolation in which a digital exposure notification system can aid. In particular, the beginning of such cross-state collaborations is evident in the consortia of state governments such as the Western States Pact and a multi-state council in the northeast, both working together to coordinate their responses. We expect that coordinated deployments of digital exposure notification applications and public policies may lead to more effective epidemic control as well as more efficient use of limited testing and isolation resources.

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Effective Configurations of a Digital Contact Tracing App: A report to NHSX

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Background

Digital contact-tracing is being developed in several countries to tackle the SARS-CoV-2 pandemic. Manual contact tracing is too slow to reach people before they transmit, whereas the scalability and speed of a digital approach, using proximity sensors of smartphone devices, is theoretically fast enough to stop the epidemic (Ferretti et al. 2020).

The development of an app includes a technological component and an epidemiological component. The technical component needs to ensure that the proximity events are recorded with sufficient precision in different circumstances and that protection of personal health-related data is ensured throughout the process. NHSX, the European PEPP-PT project (https://www.pepp-pt.org), and the Norwegian FHI, are developing systems that are both functional and secure. Solving the technical aspect is necessary but not sufficient to secure its success. A functional contact tracing app that can successfully suppress the epidemic requires a transparent algorithm that is (1) epidemiologically sound, (2) has been assessed by simulation with extensive sensitivity analysis, and (3) can be audited and optimised as data from the app becomes available and the epidemic evolves.

The overarching objective of this report is to present simulations that will support the deployment and optimisation of digital contact tracing within an established programme of epidemic mitigation and control, and specifically to explore the conditions for success as countries prepare for exit from lockdowns. A lockdown can be regarded as a quarantine applied broadly to most of the population, excluding only key workers for example, whereas digital contact tracing can limit quarantine requests to those most at risk of transmitting the virus.

A measure of success for digital contact tracing is the extent to which it reduces onwards transmission of the virus whilst simultaneously minimising the number of people in quarantine.

The primary aim of this study is to compare the impact of different app configurations on epidemic dynamics given a plausible set of assumptions on user uptake and the technological limits of the system. The effectiveness is furthermore dependent on key epidemiological parameters like the generation time, R_0, and the percentage of asymptomatic and mildly symptomatic cases. We present sensitivity analyses, such that the effect of the intervention can be seen in a collection of simulated epidemics with a range of plausible patterns.

The secondary aim is to estimate the broader societal consequences of pursuing the intervention, in terms of numbers of people quarantined, and in particular the number of uninfected people being asked to quarantine. Half of COVID-19 infections are transmitted before the onset of symptoms (Ma et al. 2020; Ganyani et al. 2020; Ferretti et al. 2020), which is sufficient to cause a growing epidemic (i.e. even perfect isolation of all symptomatic individuals would be insufficient to stop the epidemic). Successful epidemic control of COVID-19 in a non-immune population must therefore involve isolation of some non-symptomatic infected individuals. Since these individuals cannot be distinguished from uninfected individuals at the early stages of disease, it is inevitable that some uninfected people will have to be quarantined to achieve epidemic control. This can be achieved by mass quarantine or lockdowns; however, lockdowns are entirely non-specific and cause major disruption to society and the economy. As an alternative, a contact tracing app can target timely quarantine advice to infected people, though not with perfect specificity or sensitivity. In this report we present strategies that minimize numbers of quarantined individuals while maintaining sustainable epidemic control after lockdown restrictions are lifted.

Instant identification of cases by self-reporting of symptoms is likely to be highly effective at tracing their contacts, including pre-symptomatic contacts, before they transmit. Substantial reductions in the proportion of uninfected people in quarantine can be achieved by rapid follow-up testing of index cases, which could release whole clusters of contacts. We explore different mechanisms of quarantine and release that could further reduce total numbers of individuals in quarantine, independent of testing. We use recent data from OFCOM on age-specific smartphone use, with overall use of 70% of the population. People aged over 70 have low smartphone use and are highly vulnerable to COVID-19, so we recommend continued shielding of this age group (partial lockdown). We assume no app use in children aged under 10.

With these assumptions, we find that the epidemic can be suppressed with 80% of all smartphone users using the app, or 56% of the population overall.

We end by discussing limitations of the algorithm as it is currently proposed and suggest a strategy for further optimization, using data acquired by the app after it is released. We also discuss the role that community rapid testing would have in improving the policy, resulting in fewer quarantined people than relying on self-diagnosis.

Methods

An individual-based network model of social interactions.

Contact tracing is difficult to model accurately in a simple mathematical model, because a history of previous contact events must be recalled. Therefore an individual-based model (IBM) offers the most parsimonious method for accurately capturing the effects of this intervention. Other non-pharmaceutical interventions can be modelled simultaneously in the same framework.

We simulated an urban population of 1 million individuals, chosen to represent a plausible catchment area of a single NHS trust. The demographic structure of the simulated population was based upon UK-wide census data, and the structure and sizes of households were matched to data from the *Understanding Society* survey; for example, older people tend to live together and young children tend to live with younger adults. On a daily basis all individuals in the model move between *small world networks* representing households and a second network representing either work places, schools, or regular social environments for older people. Individuals also enter random networks representing public transport,transient social gatherings etc. Membership to each type of network is determined by age, giving rise to assortative mixing patterns. Network parameters are chosen such that the average number of interactions match age-stratified data reported in (Mossong et al. 2008). The actual number of daily interactions within random networks is drawn from a negative binomial distribution, which allows for rare super-spreading events.

The interaction networks play two roles in the IBM. The first is that inside each network, individuals can transmit the infection to each other on each day that a connection is made. Secondly, to model digital contact tracing, the past network of an infected individual is recalled and used to quarantine their contacts. The proportion of the network visible to, and informing, the intervention is set by parameters controlling coverage of the app in the population, self-diagnosis by users, compliance with the advice, drop-out rates, and the sensitivity of the technology in detecting transmission events.

Modelling SARS-CoV-2 transmission, disease progression and epidemiology

COVID-19 infections were seeded into the modelled population and permitted to spread via the interaction network. The probability of transmission is determined by the stage of infection, the network in which exposure occurred (home interactions are assumed to be twice as likely to result in a transmission compared to workplace and random network interactions), the infectiousness of the transmitter, and the susceptibility of the recipient. Susceptibility is modelled as a function of age, as is the severity of infection (see Parameter Sheet). The increase in infectiousness as a function of severity is also modelled. Individuals progress through stages of being susceptible, infected, and recovered (immune) or deceased, as depicted in supplementary figure 1.

Individuals develop symptoms after a mean of 6 days (standard deviation 2.5 days) (Backer, Klinkenberg, and Wallinga 2020; Lauer et al. 2020). An individual's infectiousness varies over the time course of their infection following a gamma distribution with mean 6 days (Ferretti et al. 2020; Ma et al. 2020; Ganyani et al. 2020). We assume 18% of individuals in all age groups remain asymptomatic (i.e. never develop symptoms) (Mizumoto et al. 2020), and the remainder are divided into severe and non-severe categories with differing proportions by age (Parameter sheet). Disease severity correlates with infectiousness (Verity et al. 2020; Lu et al. 2020; Luo et al. 2020), and rates of severe infection also vary by age (Souza et al. 2020; Yang et al. 2020). Compared to individuals with relatively severe symptoms, mildly symptomatic individuals are taken to be 0.48 times as infectious, and asymptomatic individuals 0.29 times as infectious (Luo et al. 2020). Probabilities of hospitalisation, demand for critical care, rates of recovery and progression to death are all age dependent. Hospitalised patients are removed from the interaction network. We do not currently model hospital interactions; nosocomial transmission and specific considerations for hospital workers are the subject of ongoing work.

Without intervention, COVID-19 transmission was assumed to have a generation time with mean 6 days and an epidemic doubling time of 3 to 3.5 days resulting in an R_0 of 3.4 and 3, respectively. Relationships between a broader range of these core epidemiological assumptions and the outcome of the interventions under study were explored in sensitivity analyses.

Modelling the interventions

Non-targeted interventions, including physical distancing and generalised lockdowns, were modelled along with digital contact tracing. As a baseline assumption in all interventions, 80% of symptomatic individuals self-quarantine together with their household members, irrespective of whether an individual has the app. **Individuals over 70 years old continue their quarantine after lockdown (shield group).** Symptomatic individuals quarantine for 7 days; asymptomatic household members and traced individuals quarantine for 14 days. Non-compliance with quarantine was modelled by assuming that 2% of individuals drop out of quarantine each day. COVID-19 disease is confirmed in hospital by testing hospitalised cases; there is no testing in the community.

The model assumes that the population entered a 35-day lockdown when 2% of the population became infected. During lockdown, workplace and random contacts are reduced to 20% and household contacts increase to 150% of the previous values.

The app starts contact tracing at the end of lockdown, but has already collected a 7-day memory of contacts at this point. All contacts in the model are potentially infectious contacts, in line with the assumptions being made in the app development that only longer and closer contacts will result in notification, which is biologically plausible.

We assume that only 80% of modelled contacts are registered by the app, either for technical reasons, or due to some contacts involving people not carrying their phones.

If a user self-diagnoses, contacts of the past 7 days are taken into account when calculating the probability that the contact resulted in a transmission. All individuals were assumed to self-isolate after receiving a notification (workplace and random network contacts drop to zero), with a drop-out rate of 2% per day.

We assume that each day, 0.05%, 0.2% or 0.5% of app users declare symptoms for reasons unrelated to COVID-19. This models the combined effect of non-COVID-19 infections (eg. daily probability of non-COVID-19 similar symptoms including influenza: 0.002%, (Influenza Surveillance Team, PHE 2019) and false declaration of symptoms for malicious and non-malicious reasons.

The IBM code is open source, and can be accessed on GitHub alongside a Jupyter notebook (Python-based user interface) for running the model and visualising outputs.

Results

The aim of this report is to model the development of the epidemic under a number of different scenarios involving a contact tracing app being used for targeted quarantine.

For different interventions we report the following outcomes:

- daily incidence
- cumulative incidence
- daily hospitalizations
- number of people in hospital each day
- daily ICU admissions
- number of people in ICU each day
- daily deaths
- number of people in quarantine each day
- number of tests required each day

The baseline assumptions can be found in the Method section and the appendix. Briefly, a 35-day lockdown is initiated when 1% of the population are infected. Individuals over 70 are asked to self-isolate throughout in accordance with UK policy on 'shielding', which provides additional protection to this vulnerable group who are less likely to use smartphones (OFCOM data). The app begins collecting data 7 days before the end of lockdown, and begins contact tracing when lockdown ends. When a user self-diagnoses, contacts of the past 7 days are taken into account when calculating the probability that the contact resulted in a transmission. 100% of individuals were assumed to self-isolate after receiving a notification, with a drop-out rate of 2% per day. We assume that 80% of smartphone users (56% of the population) use the app, and vary this assumption widely in the sensitivity analyses in the supplement.

We consider the following scenarios (Figure 1):

- Scenario 1:
    - No app

- Scenario 2:
    - App without recursion
    - Quarantine: index cases, their households, their contacts
    - Release: everybody after 14 days from notification

- Scenario 3:
    - App with recursion
    - Quarantine: as scenario 2 plus household members of contacts

- Release: as scenario 2

- Scenario 4:
    - App with recursion and cluster release
    - Quarantine: as scenario 3
    - Release: as scenario 2&3 plus release of an index case cluster if nobody from the cluster develops symptoms within 5 days

- Scenario 5:
    - App with recursion and testing as follow-up
    - Quarantine: as scenario 3&4
    - Release: as scenario 2&3 plus release of an index case cluster if index case had a negative test

- Scenario 6:
    - App with recursion and notification upon testing
    - Quarantine: contacts are notified only after index case tests positive
    - Release: as scenario 2&3

Figure 1: App Configurations

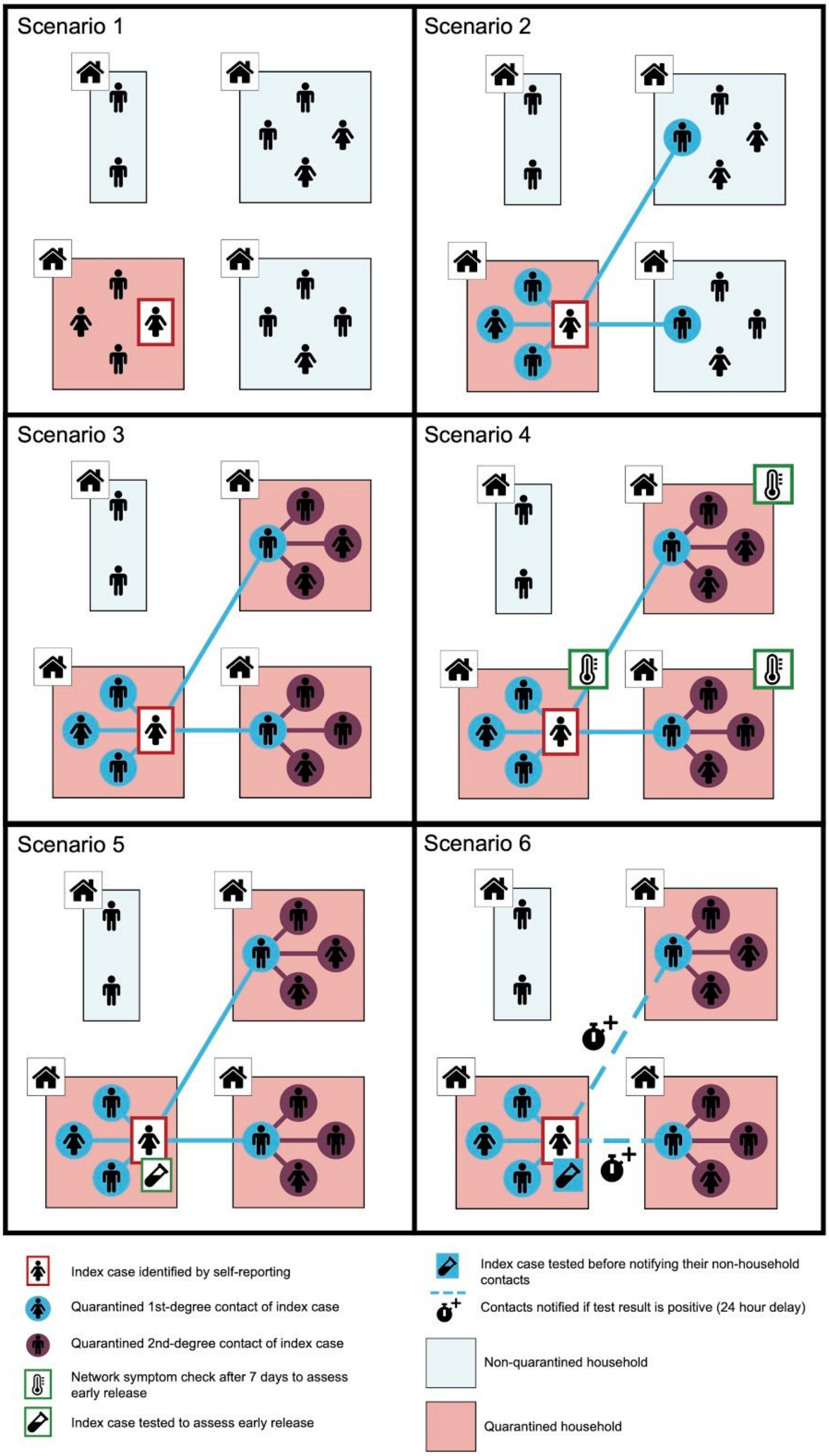
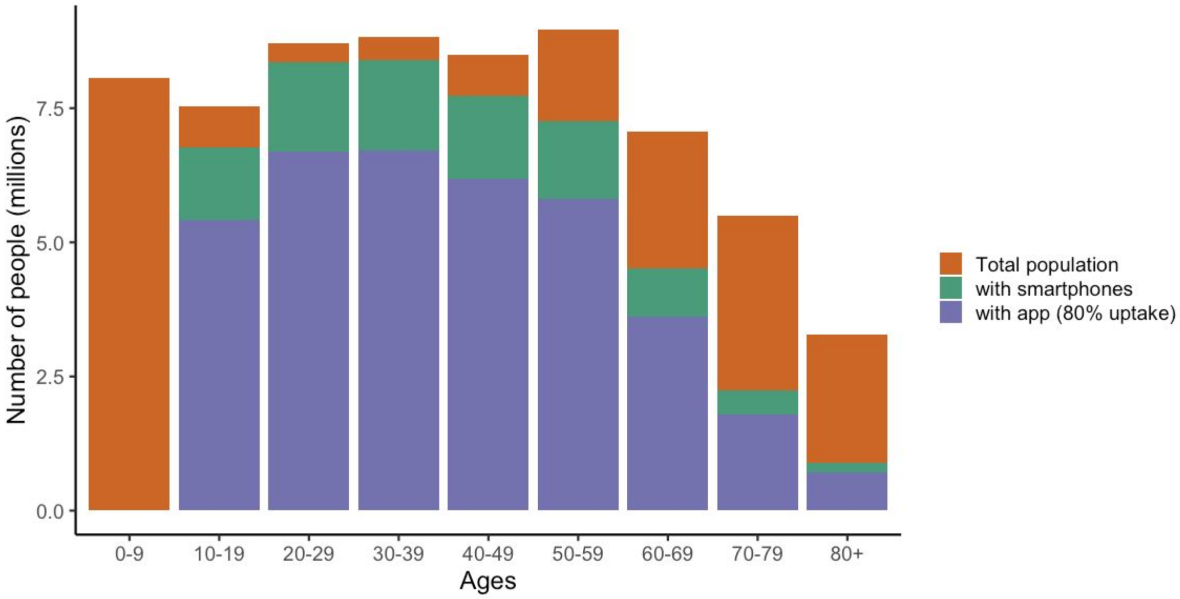


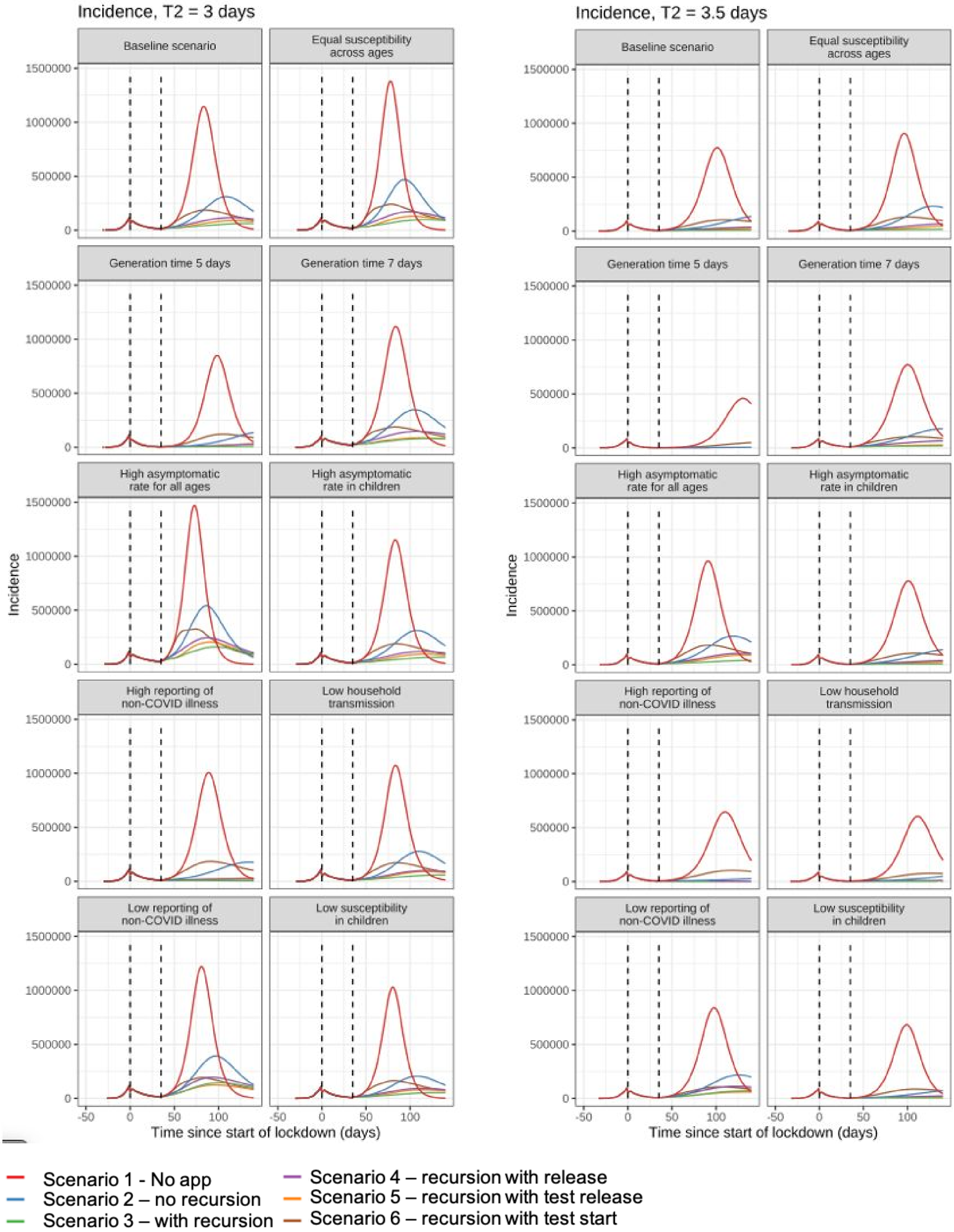
Figure 2: smartphone use by age (OFCOM), and a scenario with 80% uptake of the app amongst users, corresponding to 56% of the population. OFCOM data may under-estimate smartphone use (NHSX data).



Recent epidemiological analyses suggest that growth rates of SARS-CoV-2 may be higher than initially suspected. We explored the effects of lockdown and app-based interventions under three conditions representing slow, medium and fast epidemic growth. Simulations were calibrated on recent studies of SARS-CoV-2 transmission that report generation times in the range of 5-7 days (Ferretti et al. 2020; Ma et al. 2020; Ganyani et al. 2020). We also present all simulations for a doubling time of 3 days, resulting in an R_0 of 3.4, and a doubling time of 3.5 days, resulting in an R_0 of 3.0. In addition, we varied rates of asymptomatic infection (18%-40%), considered a range of non-COVID-19 self-diagnoses, and explored lower susceptibilities in children (ten times less susceptible than adults). Numbers on the y axis are scaled to a population of 65 million.

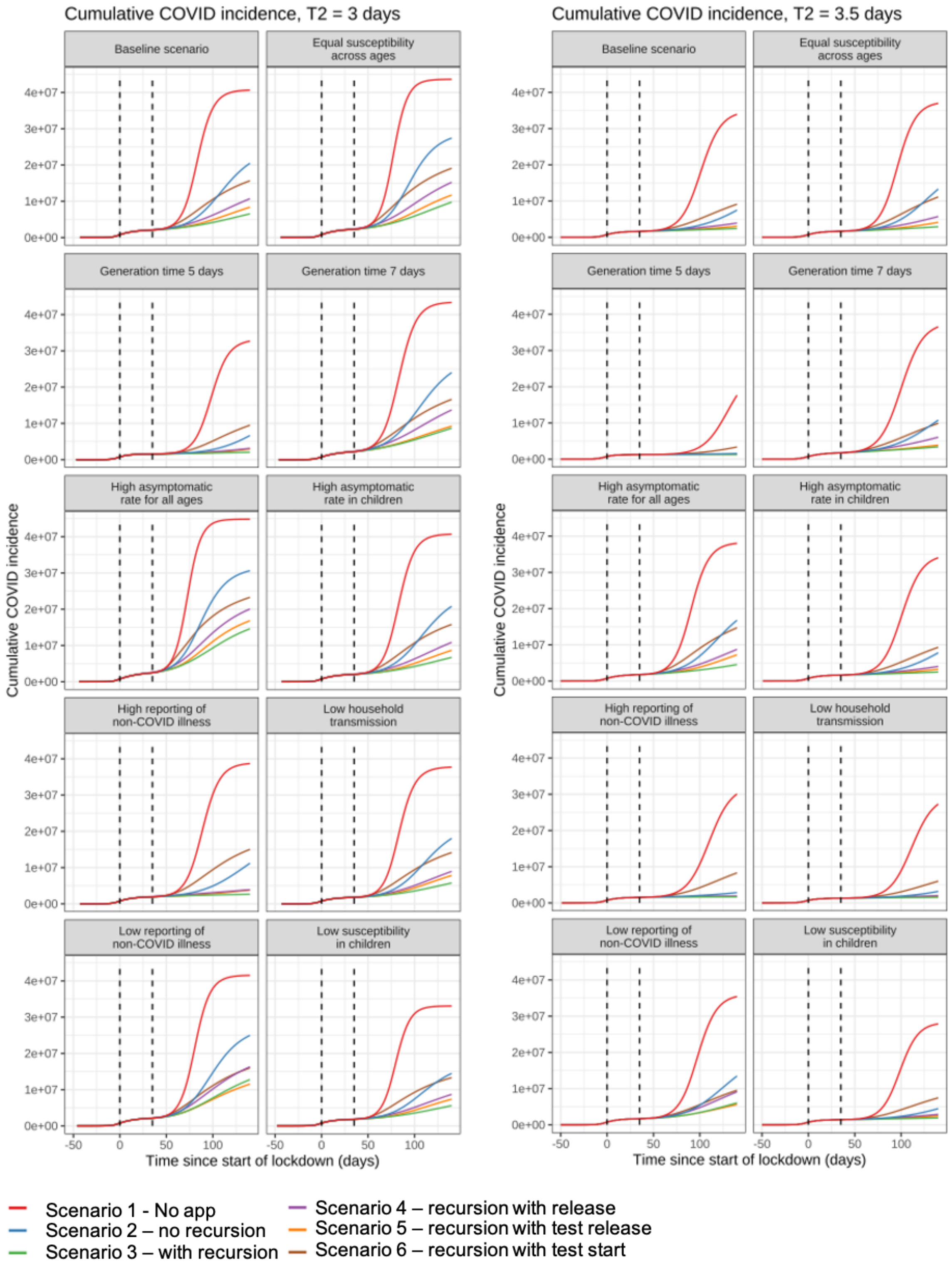
Compared to release from lockdown with only self-isolation of symptomatic individuals (Scenario 1), all configurations of the app result in a substantial reduction of new cases (Figure 3 & 4), hospitalizations (Supplementary Figure 2) and ICU admissions (Supplementary Figure 3) and in a substantial number of lives saved (Supplementary Figure 4). Direct contact tracing with the app (Scenario 2) maintains epidemic suppression only under optimistic assumptions of epidemic growth (doubling times of 3.5 days, generation time of 5 days). Allowing recursive contact tracing to household members of first-order contacts controls the epidemic under even the most pessimistic assumptions of epidemic growth (Scenario 3). However, it also quarantines the largest number of uninfected people (Figure 5), with only a 50% reduction in numbers of people quarantined compared to lockdown, assuming 0.2% of individuals initiate tracing daily for reasons unrelated to COVID-19.

Figure 3: Daily incidence.



To reduce numbers of quarantined people without causing substantially more infections we introduced a heuristic to the algorithm that released quarantined individuals if no contacts of the index developed symptoms after 5 days (Scenario 4). In practice, the effectiveness and safety of this approach would need to be improved by introducing a statistical model to calculate probabilities of clusters having COVID-19, given knowledge of individual infectious risk and of the true background rate of non-COVID-19 symptom reporting in the general populations (see optimisation section below). However, even this simple heuristic reduces the total number of people in quarantine by up to 10 million (of the total UK population).

Figure 4: Total number of people infected.



Integrating the app with community testing of index cases has the greatest impact on numbers of people in quarantine (Scenario 5). In this scenario, index cases still trigger contact tracing by self-reporting symptoms, but are then followed up with virological testing which, if negative, releases them and their quarantined contacts. High numbers of tests are needed to achieve this (Supplementary Figure 5), but the simulation highlights the potential for community testing to release significant numbers of people. In ongoing work we are exploring score-based prioritisation of testing (e.g. to clusters that involve many individuals). Improving presumptive diagnoses could also improve the specificity of quarantining and will be the subject of future work.

In the last scenario, we explore contact tracing upon positive test only, as currently planned by many countries in continental Europe. Quarantining contacts only after the index case has been confirmed positive avoids the peak of quarantine right after lockdown, but even assuming an extremely fast turn-around time for the test (24 hours from self-diagnosis to result), the delay results in more transmission from contacts in the presymptomatic phase and an overall higher number of cases and deaths compared to the scenario in which testing the index case is used to release contacts from quarantine.

Next we studied the dependence upon variable uptake of the app. We assume current levels of smartphone use, age stratified (69.5% overall, OFCOM, very low in under 10s and over 70s), and that the app is installed on a fraction of phones ranging from 0 to 1, in increments of 0.05. We find that the epidemic can be suppressed with 80% of all smartphone users using the app, or 56% of the population overall (Figure 6).

We estimated the cumulative deaths after 140 days under each scenario, assuming 0.75% infection fatality ratio, and only interventions after lockdown being app use with high adherence to notifications amongst users and continued shielding of over 70s (constant across all values of x-axis). The roughly linear dependence of the outcome on app usage reflects the combined effect of two non-linear effects acting in opposing directions, namely the quadratic dependence of proportion of contacts detected on app usage, and the well known non-linear dependence of epidemic size on R_0 (Figure 7).

Lower rates of app coverage delayed the time to a second lock-down, assuming that this would start at 1% prevalence of the total population (Figure 8).

Figure 5: Individuals in quarantine. The lock symbol refers to people quarantined during lockdown, whereas the shield symbol refers to the continuing shielding of over 70s after the end of the lockdown.

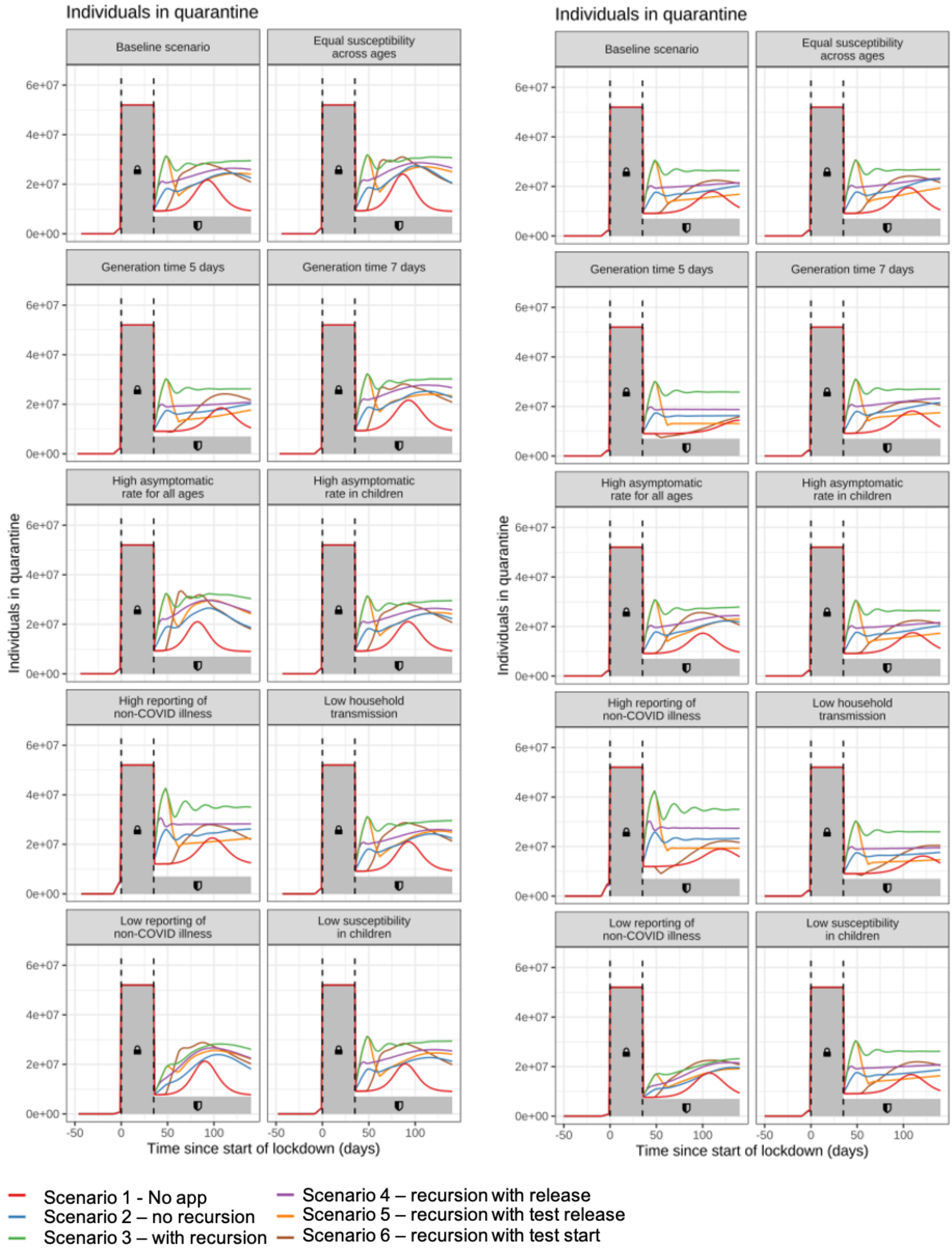
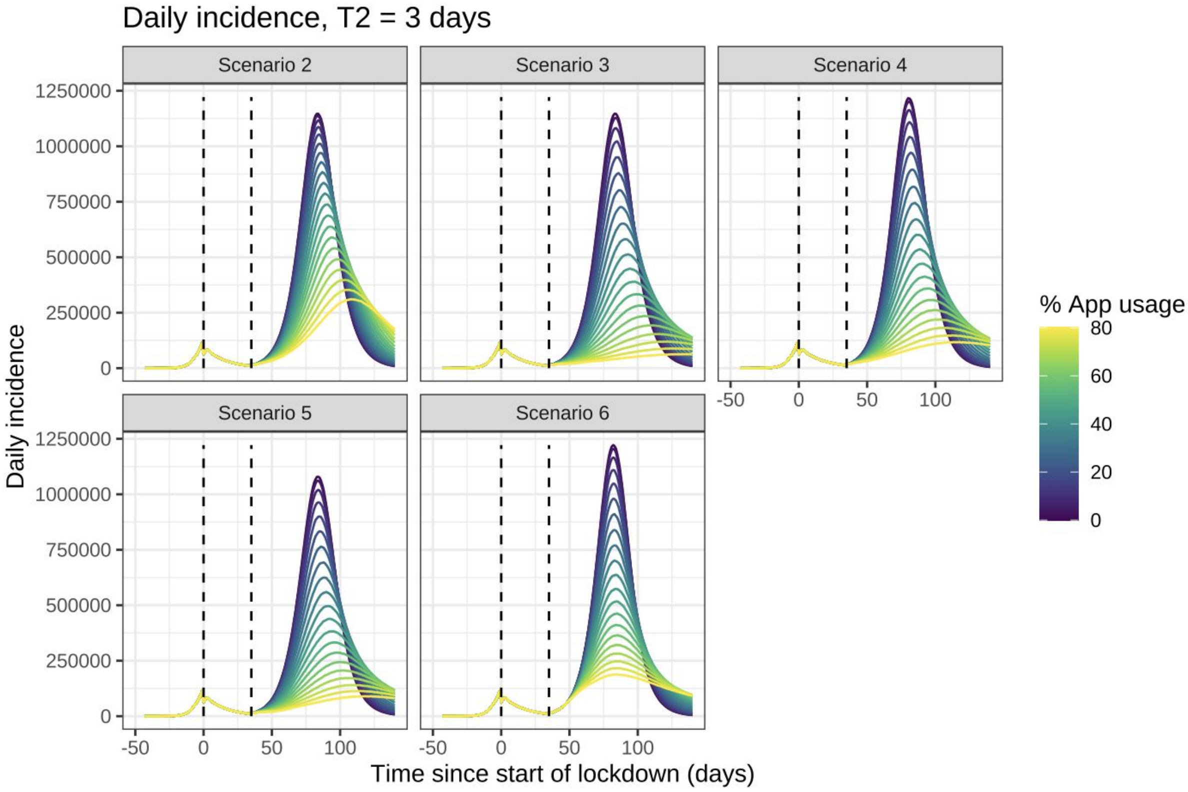


Figure 6: daily and cumulative incidence depending on varying use of the app

Doubling time 3 days:



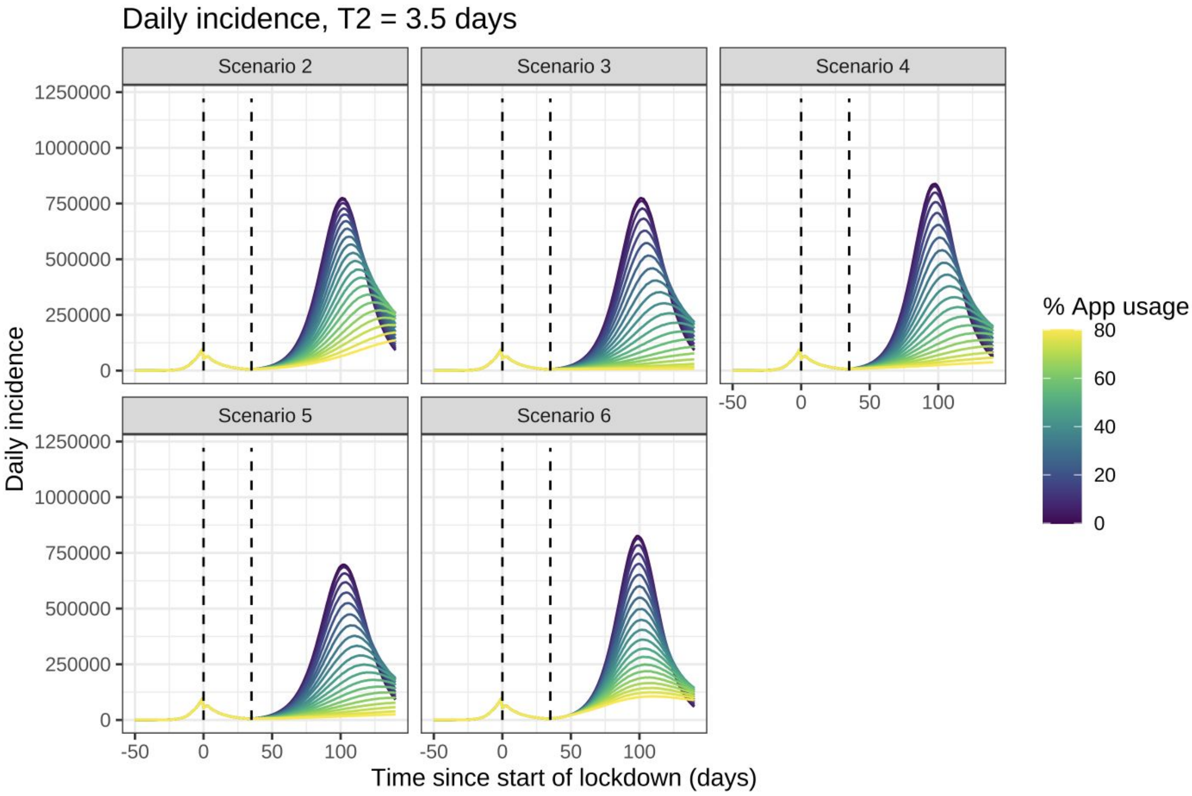


Figure 7: Cumulative deaths after 140 days

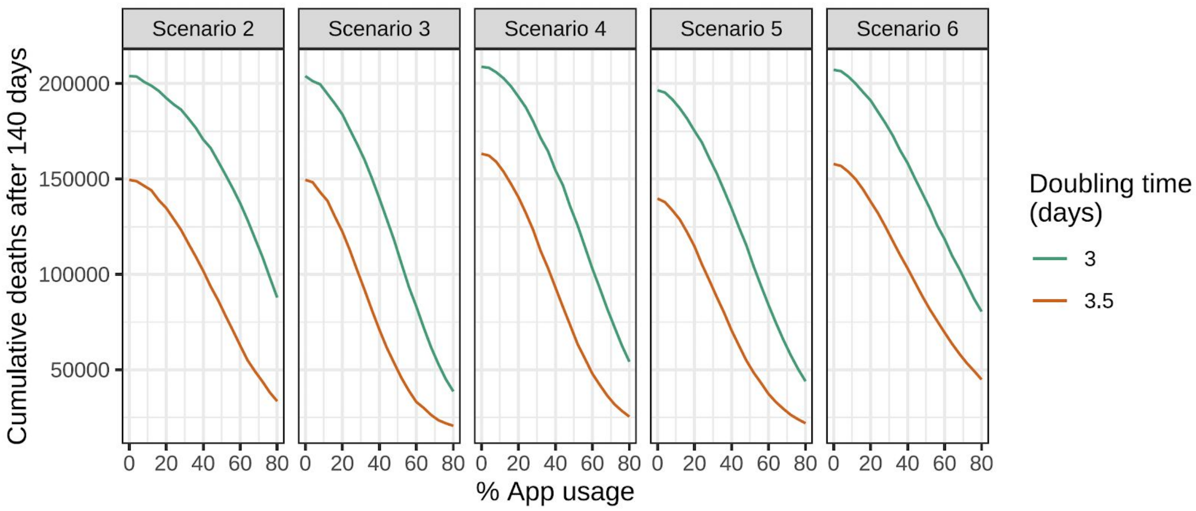
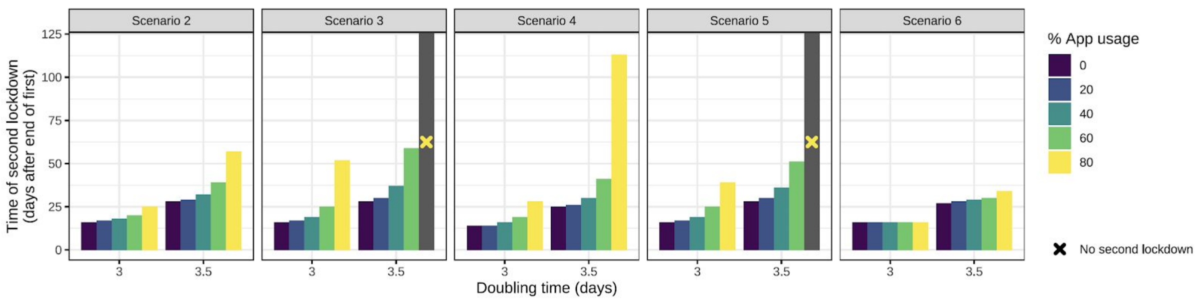


Figure 8: Continued transmission after ending first lockdown without other successful interventions would likely result in a second lockdown. For sake of argument, we assume that a second lockdown would be triggered when a 1% prevalence threshold is reached. With this trigger, the time to a second lockdown is shown as a function of each scenario and app usage. The cross symbol indicates that the criteria for second lockdown is not reached during the simulated time-period.



A plan for optimisation

Optimal functionality of the app depends on answering two questions: who should be quarantined, and when should they be released from quarantine. Our ongoing work aims to make improvements in both areas and the supplementary document (Tracing Algorithm) proposes pseudocode for its implementation.

Risk scoring

In order to optimise the configuration of digital contact tracing, we define an objective function based on a single metric: an individual infection risk score calculated from information acquired by the app. The closer the correlation between the risk score calculated from phone proximity data and the true risk of transmission, the more precise contact tracing can be applied.

The infection risk score has two components: exposure risk and transmission risk. The exposure risk between a source and a potential recipient is defined as the sum of all proximity events, each individually scored using an integral function of distance and contact duration, and multiplied by the risk that an exposure results in an infection. The latter depends on the infectiousness of the transmitter, which is principally determined by their stage of infection at the time of contact. Other factors contributing to the transmission score include (i) whether the contact occurred between household members, (ii) the presence and severity of symptoms, and (iii) the age of the source.

Incorporation of the infection risk score with a digital contact tracing app would proceed as follows: users of the app collect proximity event information, detected as low-energy bluetooth signatures, on their devices. Upon diagnosis with COVID-19 an individual's proximity events are uploaded to a central server. Each proximity event is converted to an infection risk score based on bluetooth signal strength (used to estimate distance), duration of contact, and an estimate of the individual's infectiousness, which we calculate from the interval between the onset of their symptoms and time of contact. All infectious risk scores are summed for each contact person, and contacted persons with total scores exceeding a given threshold receive notification recommending isolation.

Recursive contact tracing of individuals, to include contacts of contacts, can be decided based on the infection risk score. For example, an index-case, person A, deemed to be infectious at the time of contact with person B, could trigger immediate recursive tracing to person B's contact, to include person C; it would be reasonable to trace and isolate person C immediately if they had prolonged contact with patient B in their infectious phase.

Risk scoring can be used to increase the safety of the app by controlling the mean number of quarantine notifications initiated from a single index case. Setting thresholds on a population mean still allows for rare outlying events (e.g. superspreading events). Conversely, placing a hard threshold on distance or on type of contact could potentially create uncontrolled behaviours. Risk scoring reduces this problem but still allows the number of contacts to vary greatly between different users. We propose that the most epidemiologically reasonable and predictable approach to providing notifications is to start from the ranking of all contacts of all cases, and to place a cut-off such that the mean number of notifications per person is known.

Once the app has been running for some weeks, the risk scoring method can be improved by analysing data acquired by the app, such as follow-up clinical data and test results of traced individuals. This would optimize performance of the app, and improve epidemiological understanding and general public health advice. For example, it would be possible to test the relative importance of very long contacts, such as may be experienced at home, compared to shorter contacts; it would be possible to test the distance-dependence of contacts, or compare inside/outside contacts. Machine learning approaches could also be used to improve predictions. The better the predictions of what constitutes a high-risk contact, the better the accuracy with which notifications to quarantine can be targeted.

Smart release from quarantine using network information

Another area that can improve as the app is used is the speed of release of clusters of quarantined individuals. This can be done very effectively by testing the index case, as shown in the results above (scenario 5), but this requires approximately 100,000 tests per day for this purpose for the UK. In the absence of a sufficiently large capacity for community testing, we are exploring options to release a cluster originating from an index case after a given period if none (or a low percentage consistent with background rates of false reporting and non-COVID-19 symptom reporting) of the individuals in the cluster has experienced symptoms in this period, indicating that the index case was likely to be uninfected when the cascade was triggered. If a moderate capacity for community testing is available, the contact information can also be used to assess which index cases should be tested with priority in order to safely release the highest number of individuals from quarantine.

Discussion

This report demonstrates that digital contact tracing has the potential to make a substantial impact in suppressing the SARS-CoV-2 epidemic. Even under pessimistic assumptions of very rapid rates of epidemic growth, high rates of uptake of the app could contribute to epidemic containment, and release the majority of individuals from quarantine at the end of the current lockdown. Low rates of app use will result in resurgence of the epidemic and the need for further lockdown. With low rates of uptake, digital contact tracing at least delays the interval between lockdowns (ongoing simulations).

Compared to previous reports, we have adjusted our modelling to account for age differences in infection rate and age differences in smartphone use, and to account for faster doubling times in Europe (higher R_0). In order to maintain low mortality with use of app-based digital contact tracing, we recommend continued lockdown (shielding) of people aged over 70 - a group with assortative mixing, low smartphone use (approximately one quarter), and high COVID-19 mortality. We also assume no use of the app in children aged under 10. With these assumptions, we find that the epidemic can be suppressed with 80% of all smartphone users using the app, or 56% of the population overall.

Our individual-based model can be easily reparameterised to evaluate alternative configurations of the app and combinations of non-pharmaceutical interventions, and physical distancing assumptions, under different epidemic scenarios. The model can also be parameterised for use in other countries, using country-specific data on household composition and contact frequencies.

We previously demonstrated that rapid contact tracing was essential in reaching individuals before they transmit: delaying contact tracing by even half a day from onset of symptoms can make the difference between epidemic control and resurgence.

Testing improves specificity over presumptive self-diagnoses, but sensitivity is low in early pre-symptomatic infection. Furthermore, prolonged test turnaround times and low capacity for testing limit its current use for quarantining individuals. However if testing can be scaled up and sped up, it could be a valuable addition to the digital contact tracing process, especially as the number of new infections is reduced.

Testing index cases after they self-report can also be used to ensure the quick release of false positive clusters: if the index case tests negative, all their contacts can be released shortly after they start quarantine. Starting the contact tracing only after a positive test is less effective at suppressing the epidemic, as crucial time is lost in which contacts are already infectious.

This report provides options for a starting configuration of a contact tracing app. The algorithm behind the app can be adjusted to reflect policy changes, e.g. the introduction of more wide-spread testing. It is to be expected that the optimal solution will likely involve a number of successive scenarios to reflect an early need to capture as many infections as possible and a later need to avoid quarantining of too many people as the epidemic declines and reintroductions are monitored.

The accuracy with which bluetooth low-energy signatures can be converted to useful proxies of transmission risk is currently uncertain. By following up subsets of quarantined clusters with testing, the parameters, algorithms and functions that define individual infection risk can be rapidly refined, improving both the sensitivity of the platform (more infected people in quarantine - faster epidemic control), and specificity (fewer uninfected people in quarantine - a stronger economy and faster return to normal society).

Under current PHE guidance, manual contact tracing requires cases to list close contacts over the past 7 days that were within 2 metres and lasting 15 minutes or more. In practice this serves as an *aide memoire* rather than a strict guide, and implementation within the app could lead to unexpected consequences, and could miss transmissions resulting from frequent shorter contacts that do not meet the definition individually. In a previous report, and as part of ongoing work, we suggest that duration of contact, proximity of contact, number of contacts, time of contact in relation to symptom onset, location of contact (household vs non-household), age-band of sources and recipient, and severity of symptoms in index cases, should all be considered in determining the individual infection risk. Basing all quarantining and contact-tracing decisions on individual risk, once the app has acquired sufficient data to understand and test the relevance of this risk, is likely to result in better performance of the app.

A key limitation of this report and the current version of our model is a lack of consideration of hospitals and health care workers. Nosocomial transmission in hospitals is likely to continue even throughout lockdowns, and this could continually seed infections into the population. Healthcare workers come into contact with infected individuals on a daily basis and would not be able to use the app without special configuration. In-depth modelling of hospital transmission and interactions with the wider community is the subject of ongoing work.

Another major limitation of our study is that, with the exception of the shielding of over 70s, we consider app-based contact tracing in the context of social mixing that is identical to the pre-lockdown period. It is plausible relaxation of a lockdown may result in some continued social distancing, in which case the scenarios here could be pessimistic about epidemic resurgence.

There are no plans currently to record location data. Location data could inform epidemiological risk scoring for cases of environmental contamination. It is not currently known to what extent this is important, though our working model is that this accounts for <10% of transmissions (Ferretti et al).

We do not address the ethical arguments for and against digital contact tracing in this document. We set out the requirements for ethical implementation previously (Ferretti et al) and have further developed this discussion here:
https://github.com/BDI-pathogens/covid-19_instant_tracing/blob/master/The%20ethics%20of%20instantaneous%20contract%20tracing%20using%20mobile%20phone%20apps%20in%20the%20control%20of%20pandemics.pdf

An app is a tool for anonymously and instantaneously communicating information from index cases to their past contacts. The effectiveness of the policy in controlling the epidemic is dependent on people's response to the messages; the app alone should not be seen as an intervention independent of widespread public health activities focused on appropriate use and response, and will require trust in the system.

In contributing to epidemic control, app-based contact tracing should not be considered separate from other public health interventions such as testing, physical distancing and appropriate PPE. Conventional contact tracing may be used to validate the approach, and to enhance it. And of course, the fewer infected cases there are, the more resources can be spent preventing transmission from each of them.

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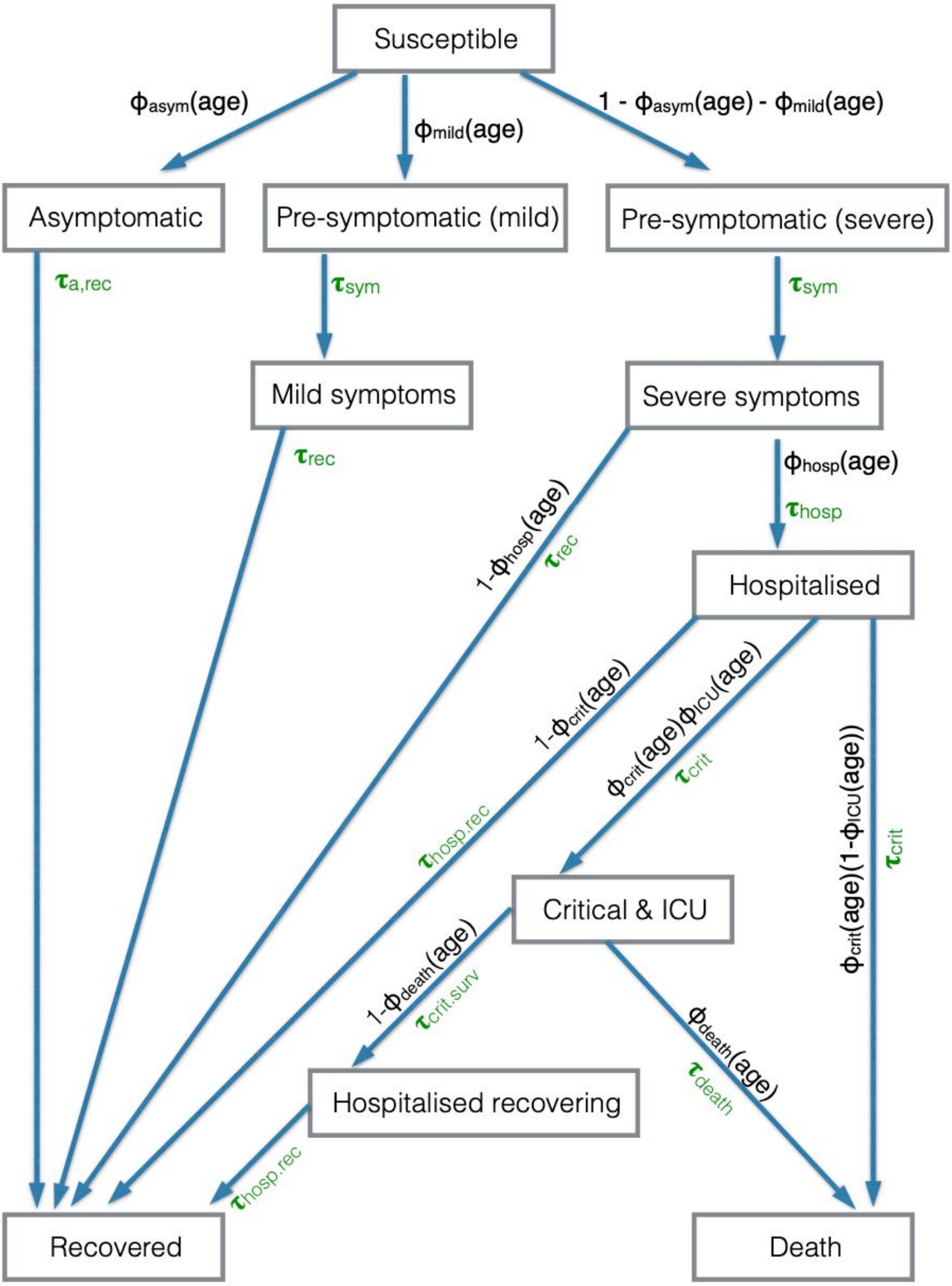
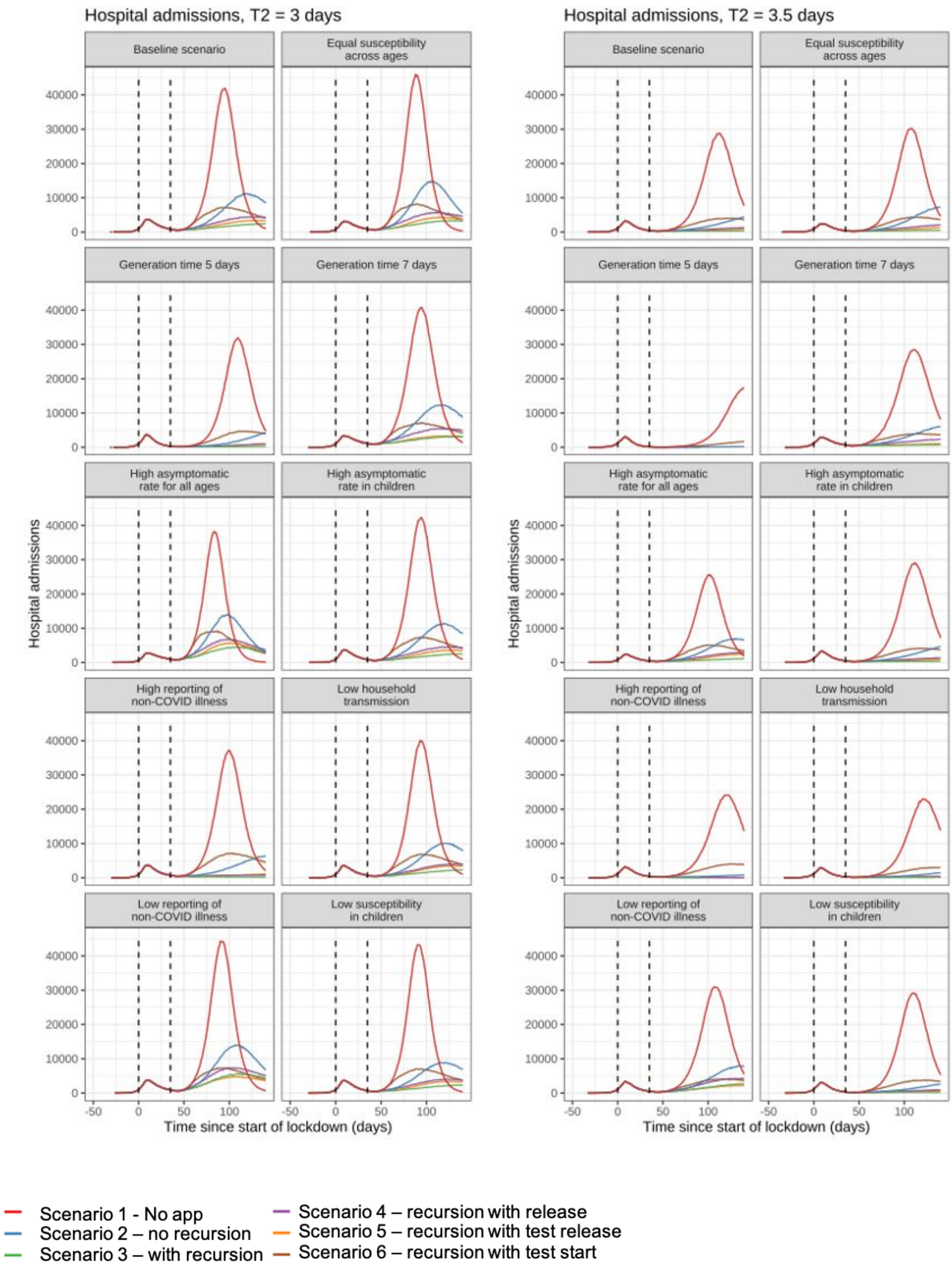
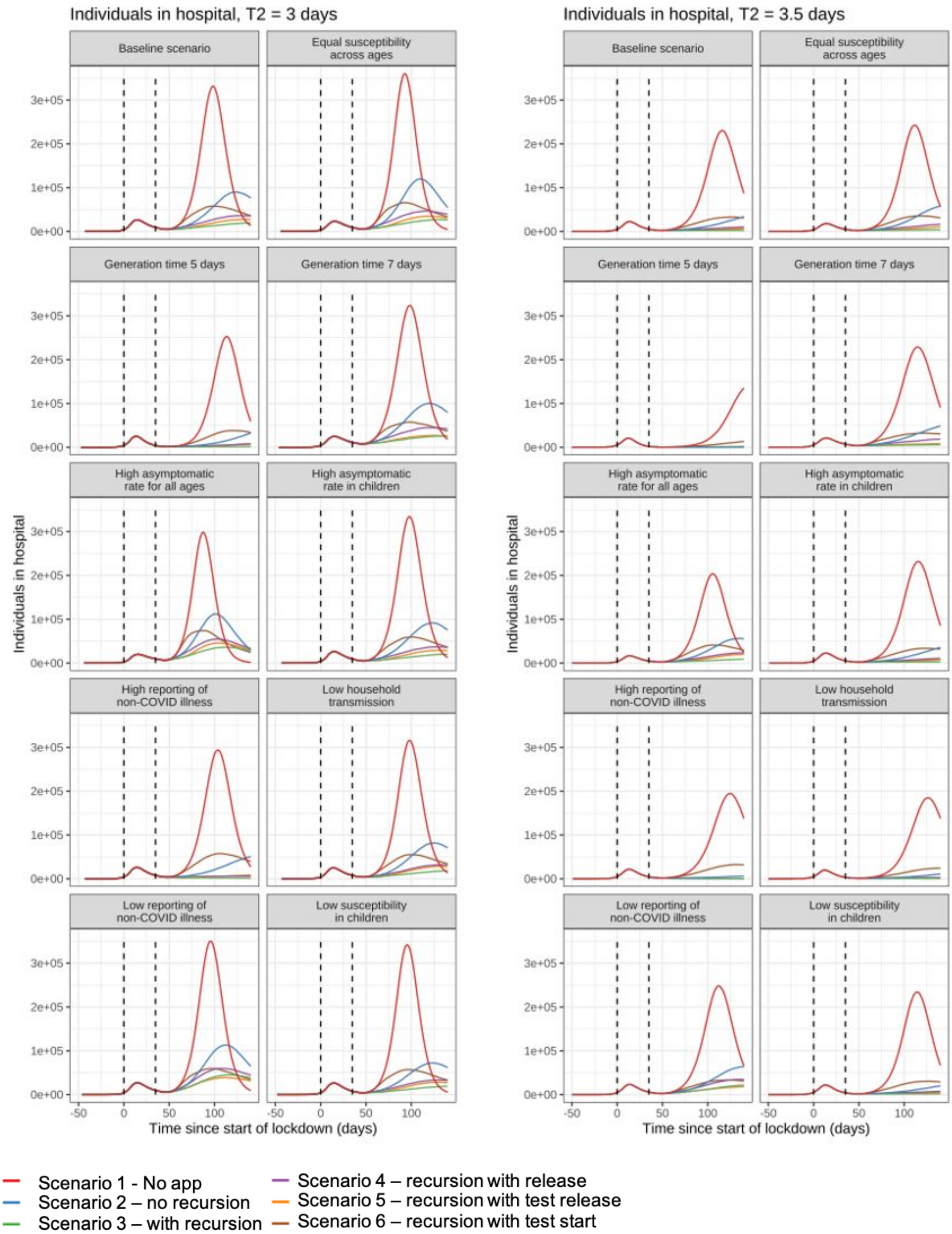


Supplementary Figure 1: The disease status of an individual and the probability and time distribution of transitions. φ_{state}(age) variables are age-dependent probabilities of transition to a particular state when there is a choice. τ_{state} variables denote the time taken to make the transition to different states.

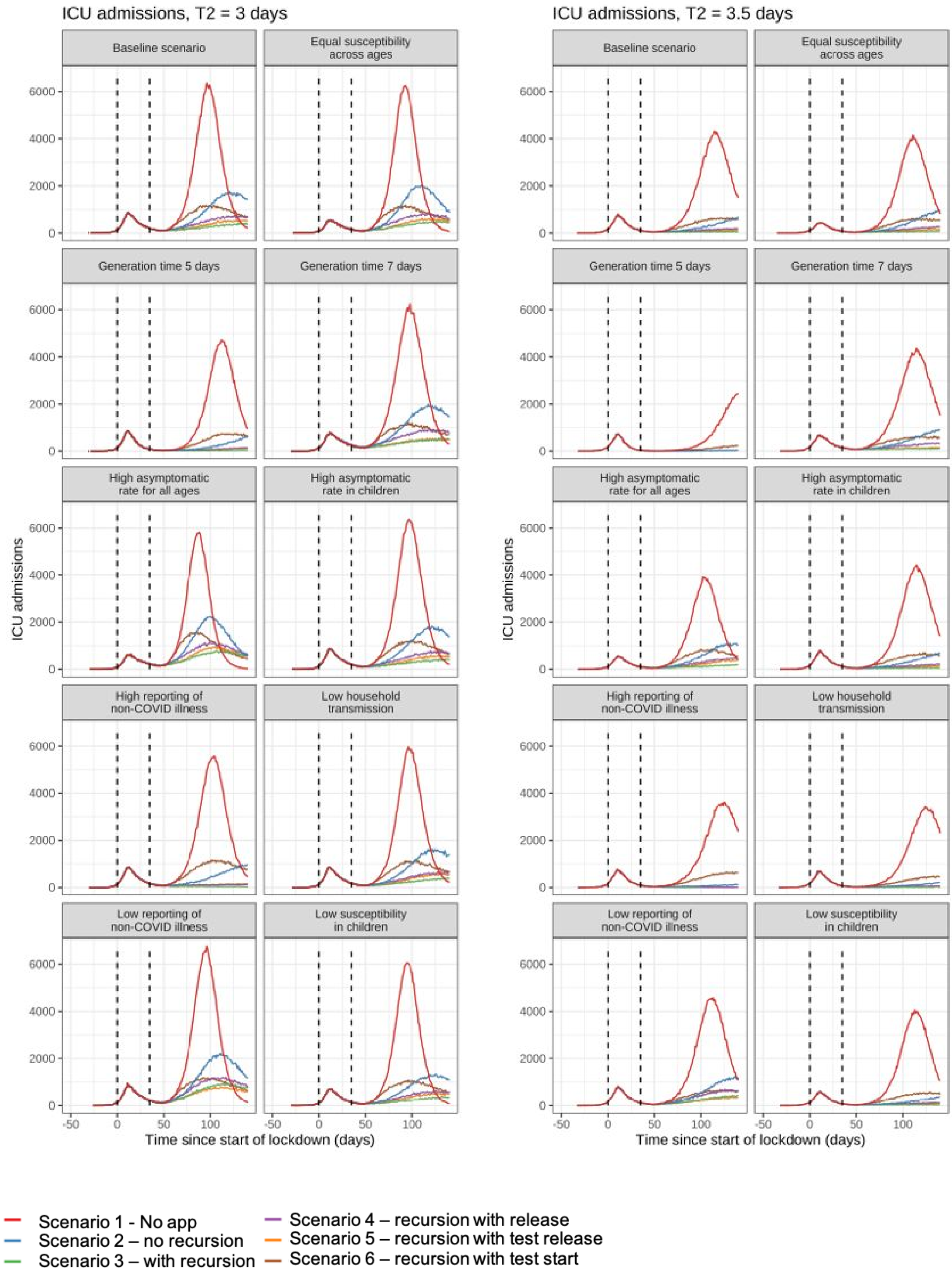
Supplementary Figure 2A: Daily hospital admissions.



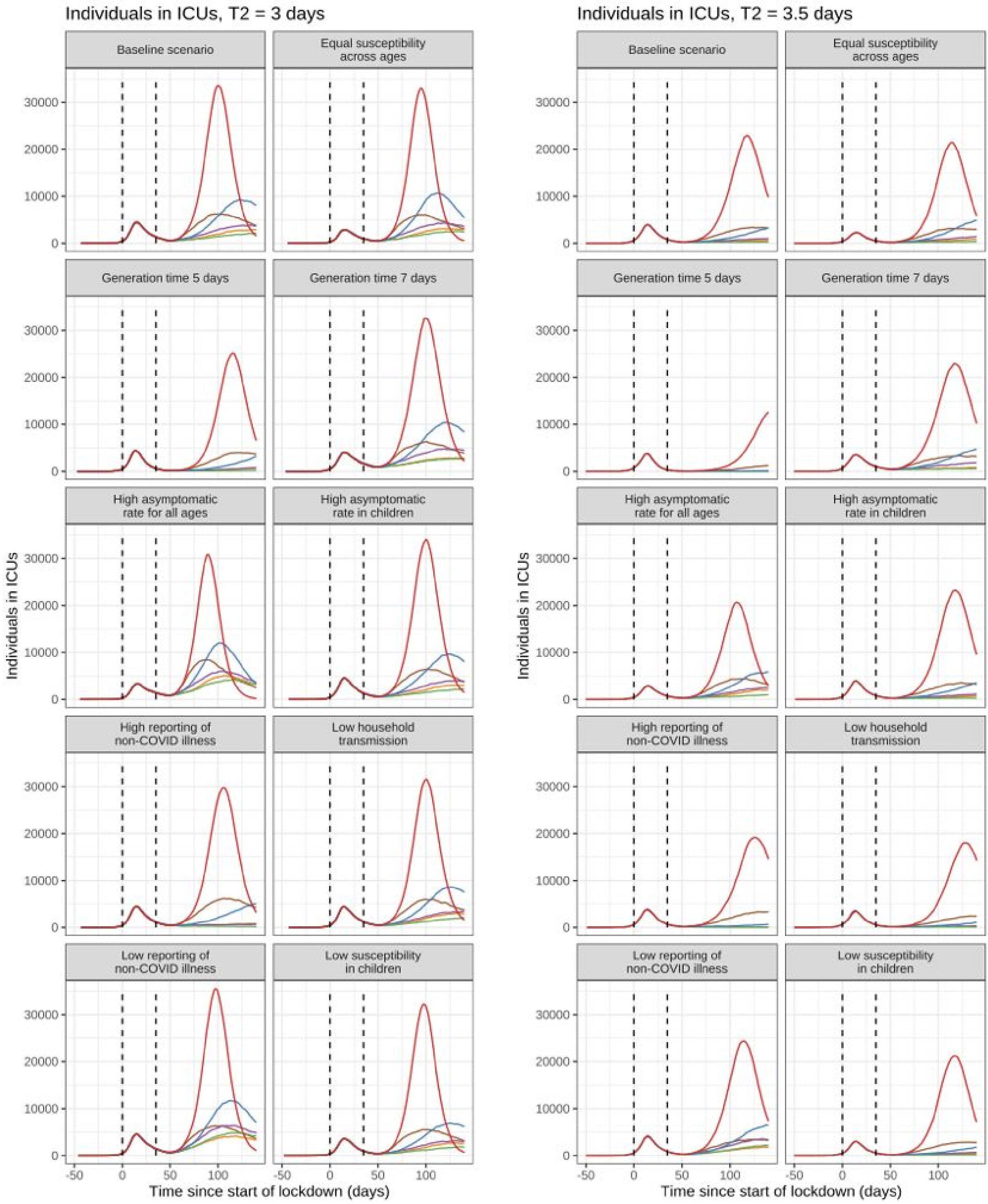
Supplementary Figure 2B: Individuals in hospital



Supplementary Figure 3A: ICU admissions.



Supplementary Figure 3B: People in ICU



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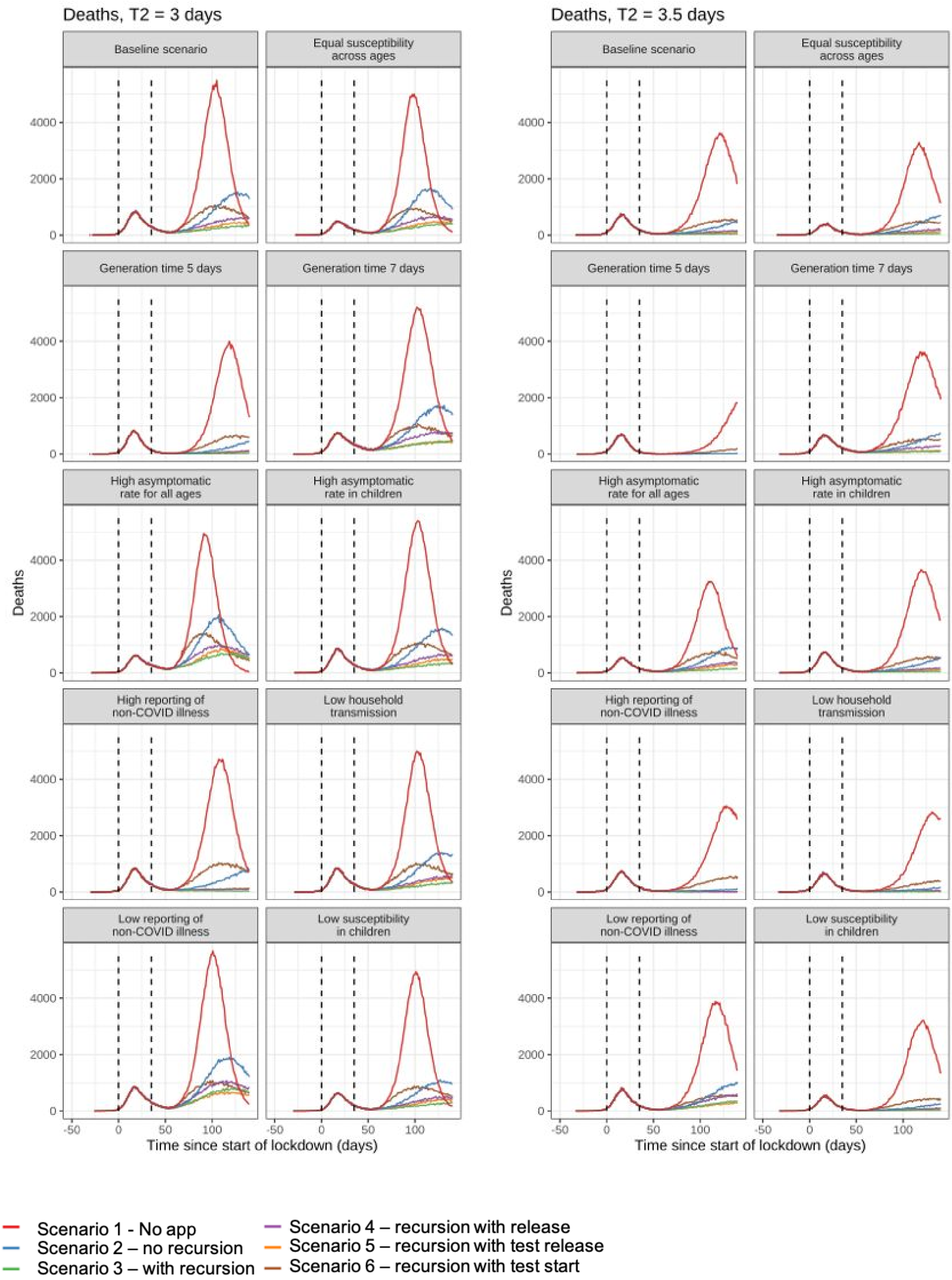
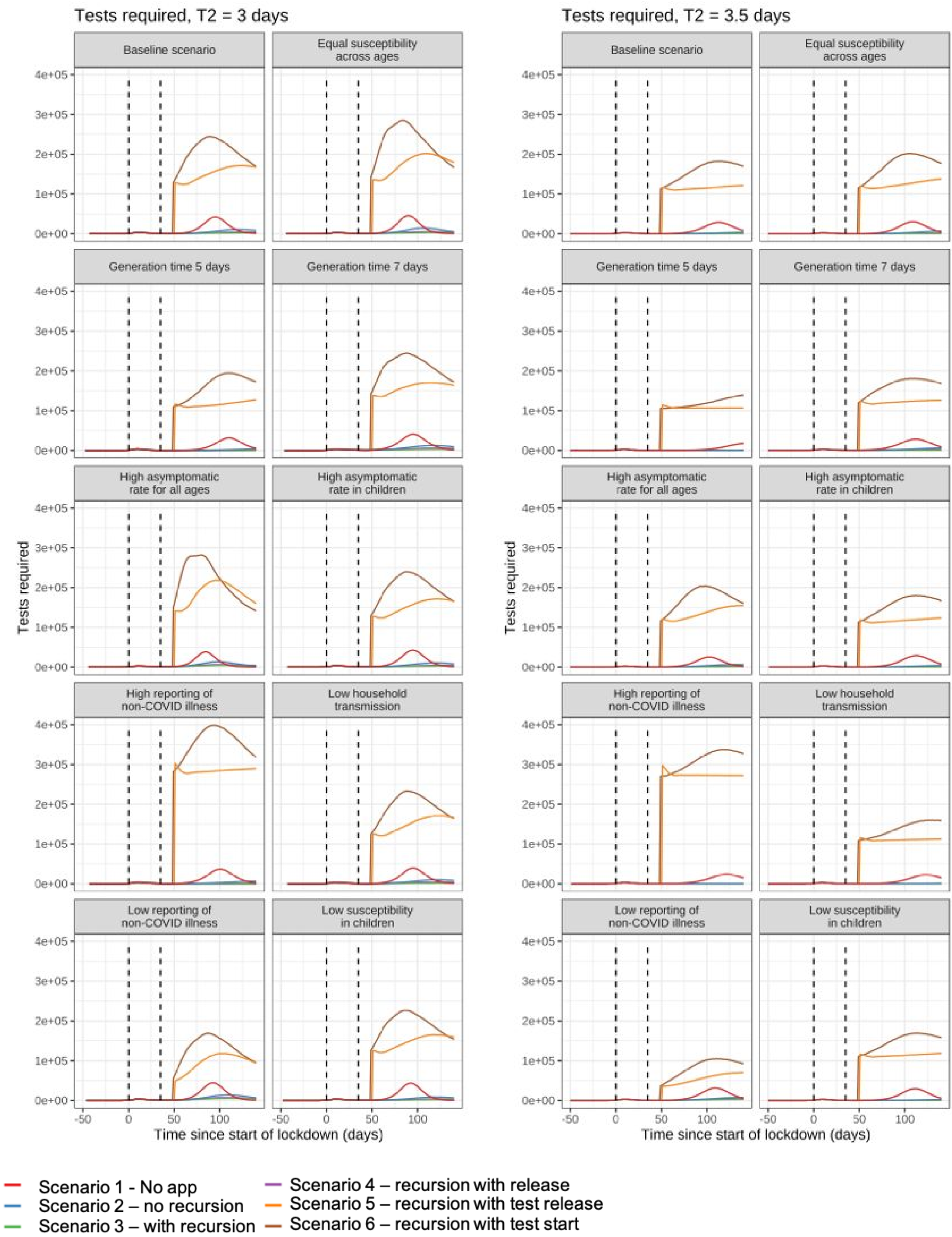
Scenario 1 - No app
Scenario 2 – no recursion
Scenario 3 – with recursion
Scenario 4 – recursion with release
Scenario 5 – recursion with test release
Scenario 6 – recursion with test start

Supplementary Figure 4: Daily deaths.



Supplementary Figure 5: daily number of tests needed. Doubling time of 3 days.



Supplementary Figure 6: Cumulative infections after 140 days.