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
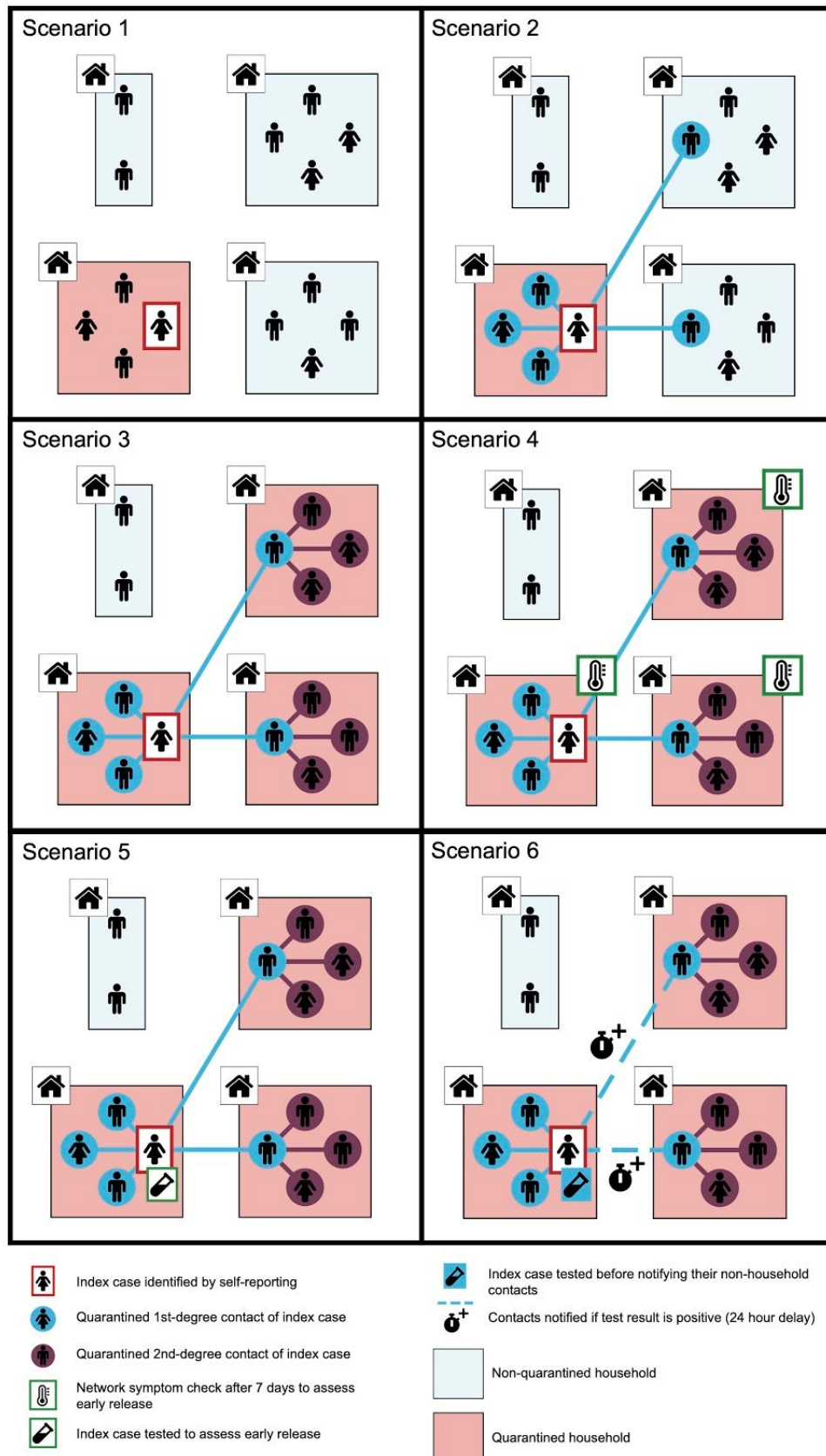
Figure 2: smartphone use by age (OFCOM), and a scenario with 80% uptake of the app amongst users, corresponding to 56% of the population. OFCOM data may under-estimate smartphone use (NHSX data).
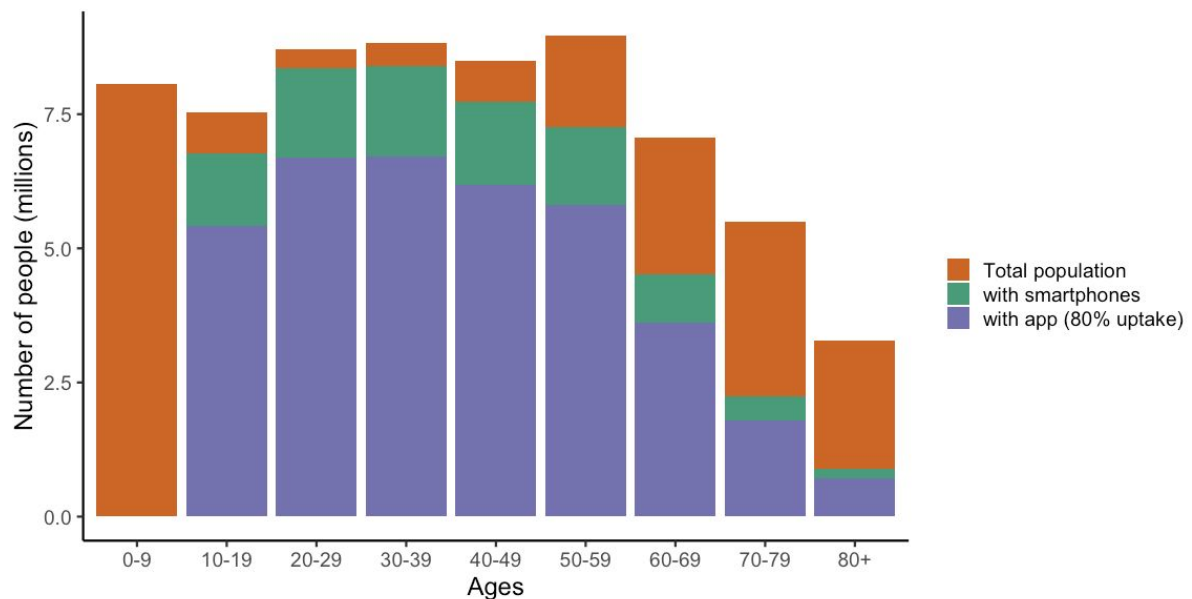
Recent epidemiological analyses suggest that growth rates of SARS-CoV-2 may be higher than initially suspected. We explored the effects of lockdown and app-based interventions under three conditions representing slow, medium and fast epidemic growth. Simulations were calibrated on recent studies of SARS-CoV-2 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.
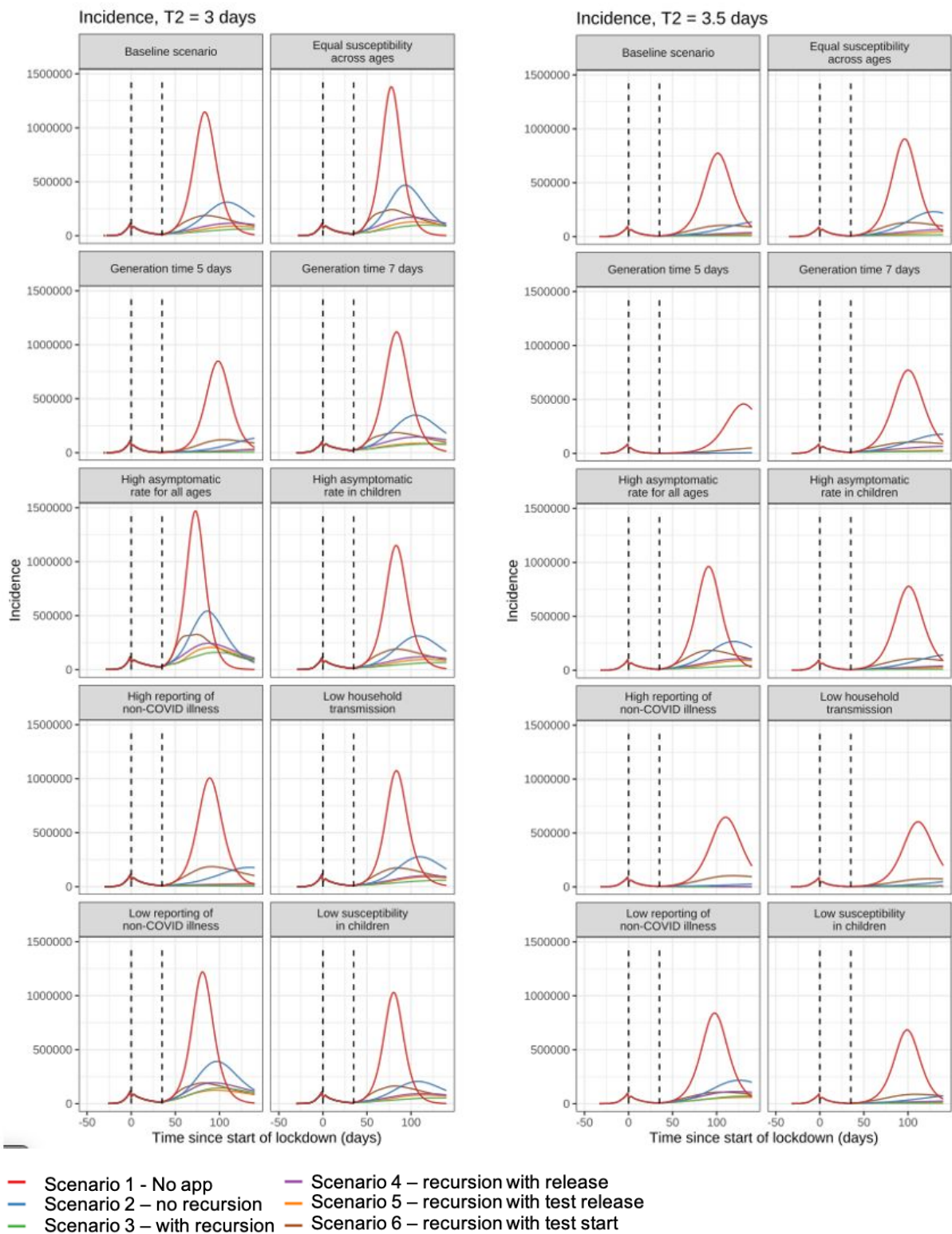
To reduce numbers of quarantined people without causing substantially more infections we introduced a heuristic to the algorithm that released quarantined individuals if no contacts of the index developed symptoms after 5 days (Scenario 4). In practice, the effectiveness and safety of this approach would 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.
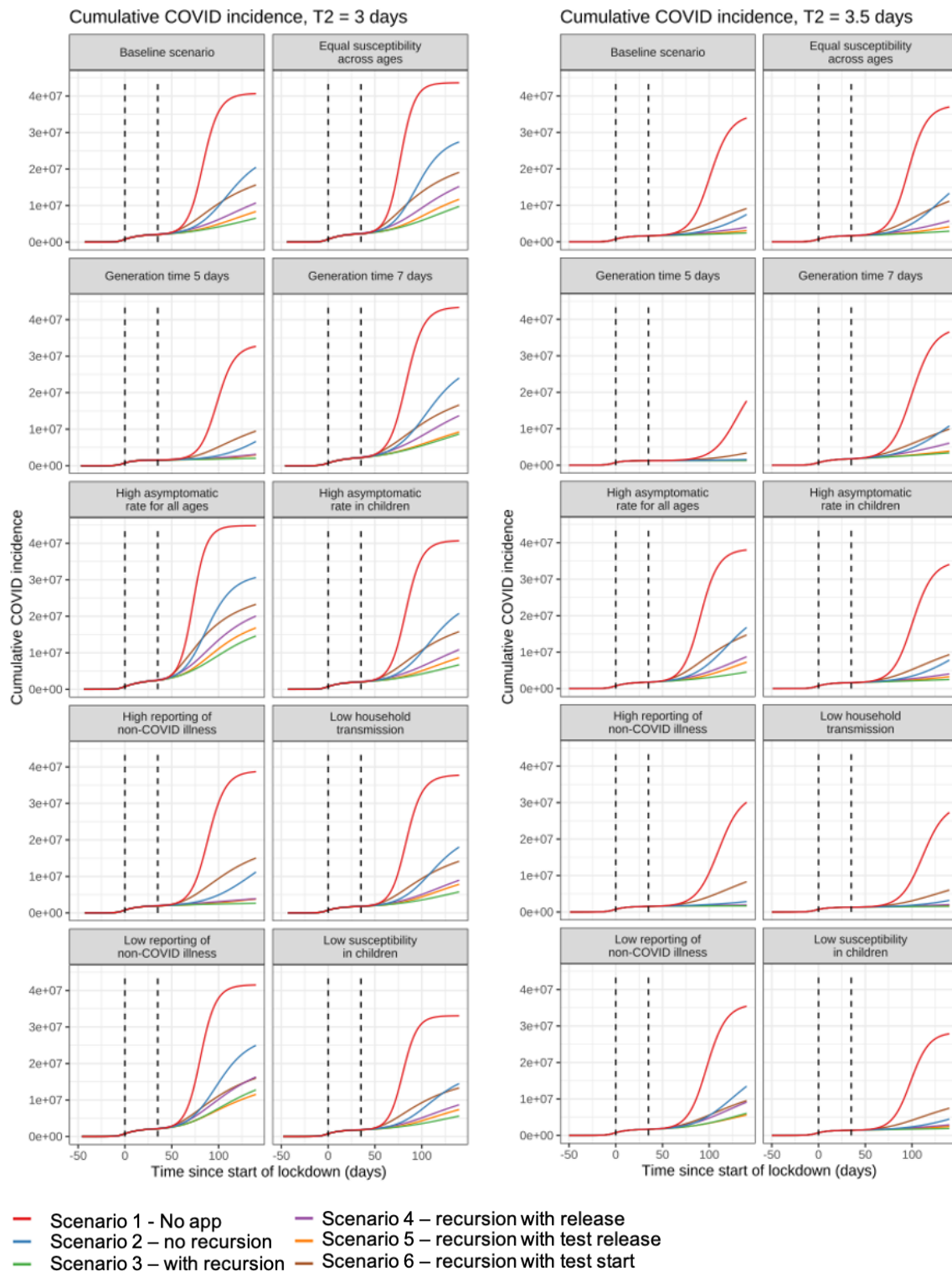
Integrating the app with community testing of index cases has the greatest impact on numbers of people in quarantine (Scenario 5). In this scenario, index cases still trigger contact tracing by self-reporting symptoms, but are then followed up with virological testing which, if negative, releases them 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.
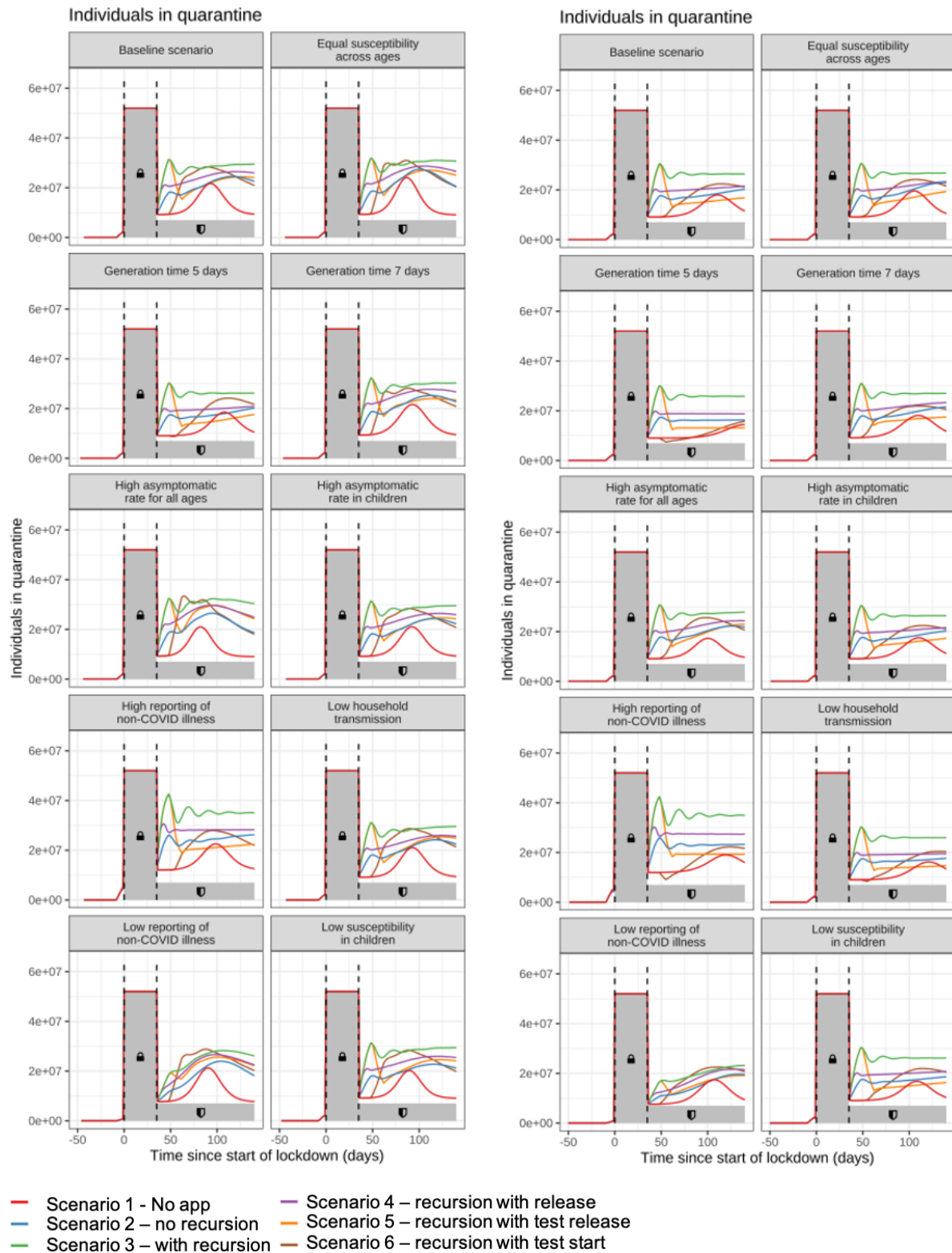
Figure 6: daily and cumulative incidence depending on varying use of the app
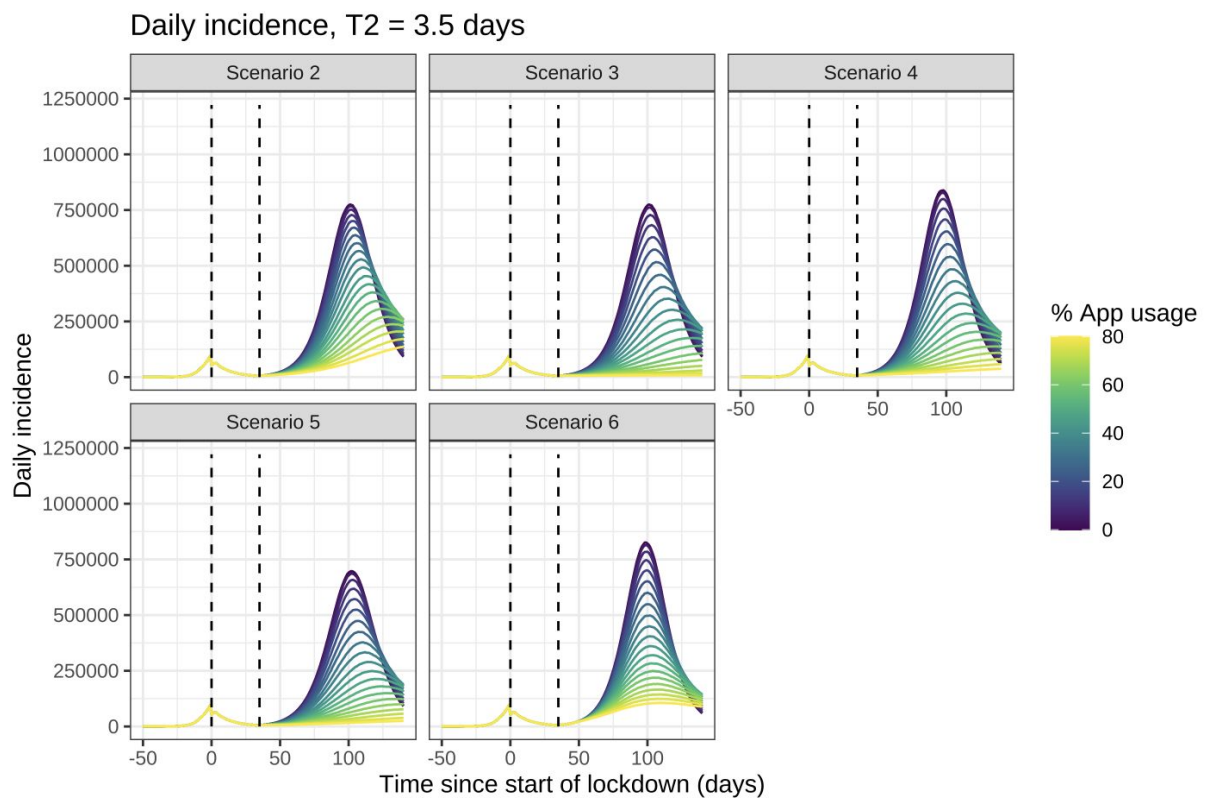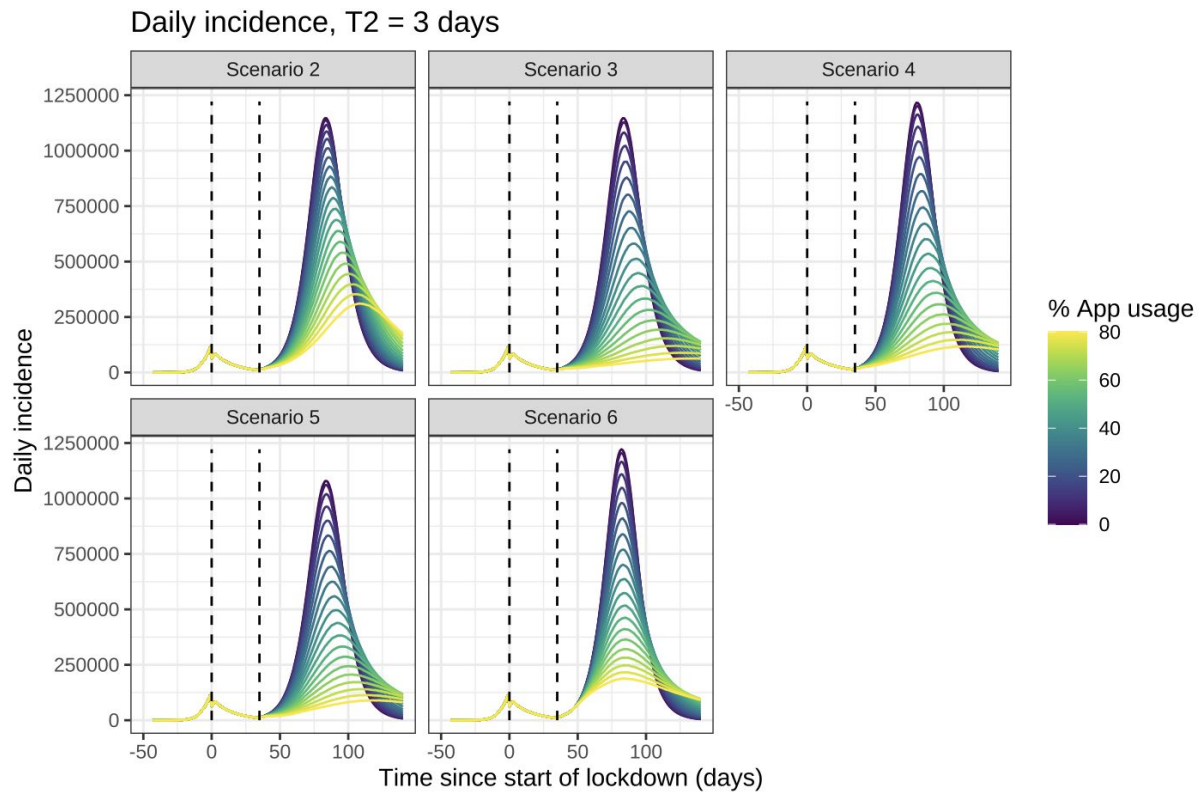Doubling time 3 days:

Daily incidence, T2 = 3 days

Daily incidence, T2 = 3.5 days

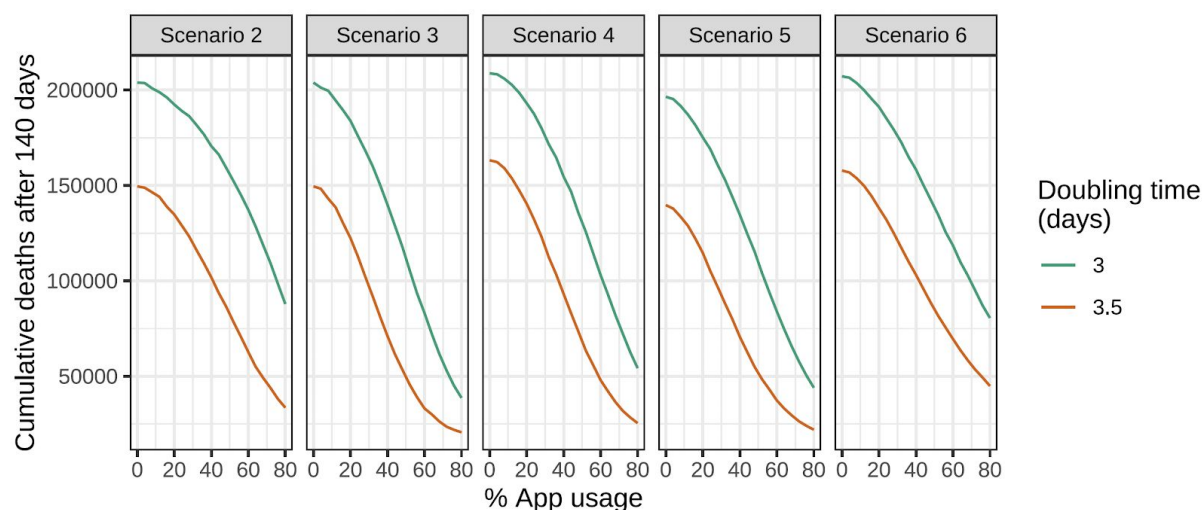**Figure 7:** Cumulative deaths after 140 days

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.
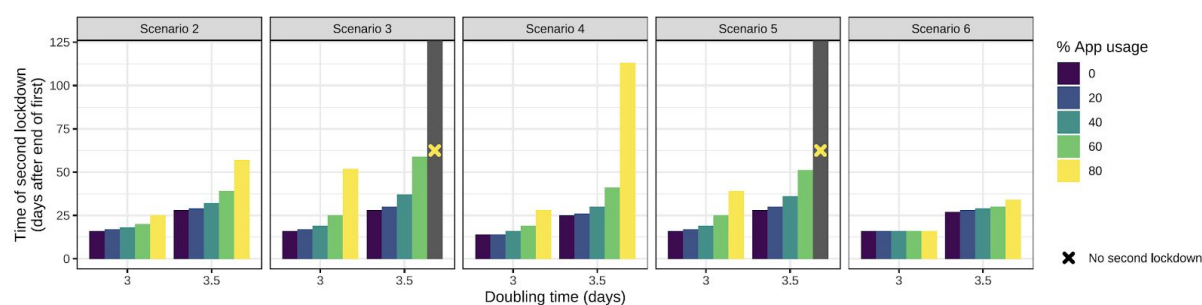
A plan for optimisation

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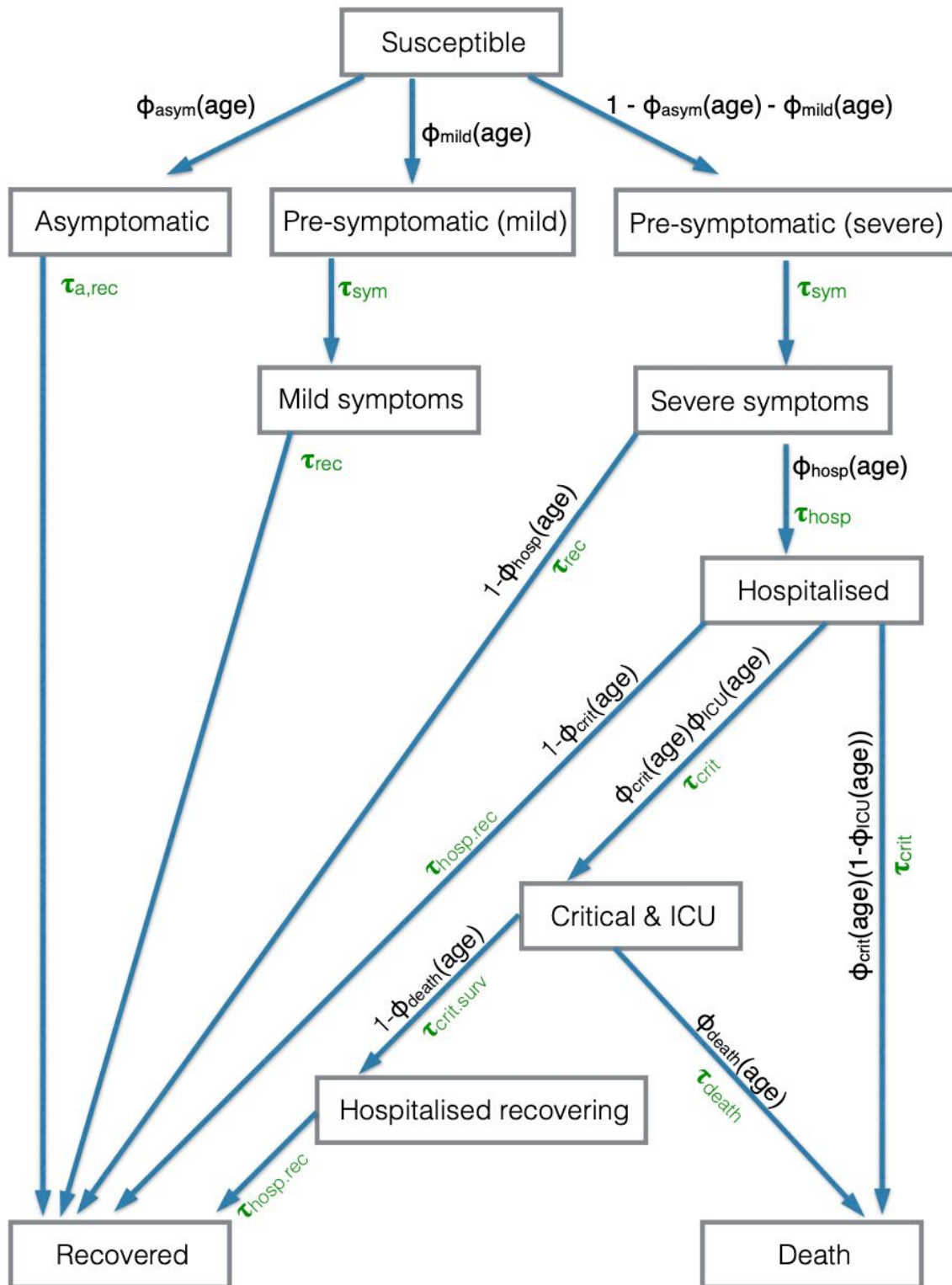
**Supplementary Figure 1**: The disease status of an individual and the probability and time distribution of transitions. $\varphi_{state}(age)$ variables are age-dependent probabilities of transition to a particular state when there is a choice. τ_{state} variables denote the time taken to make the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

Supplementary Figure 2A: Daily hospital admissions.
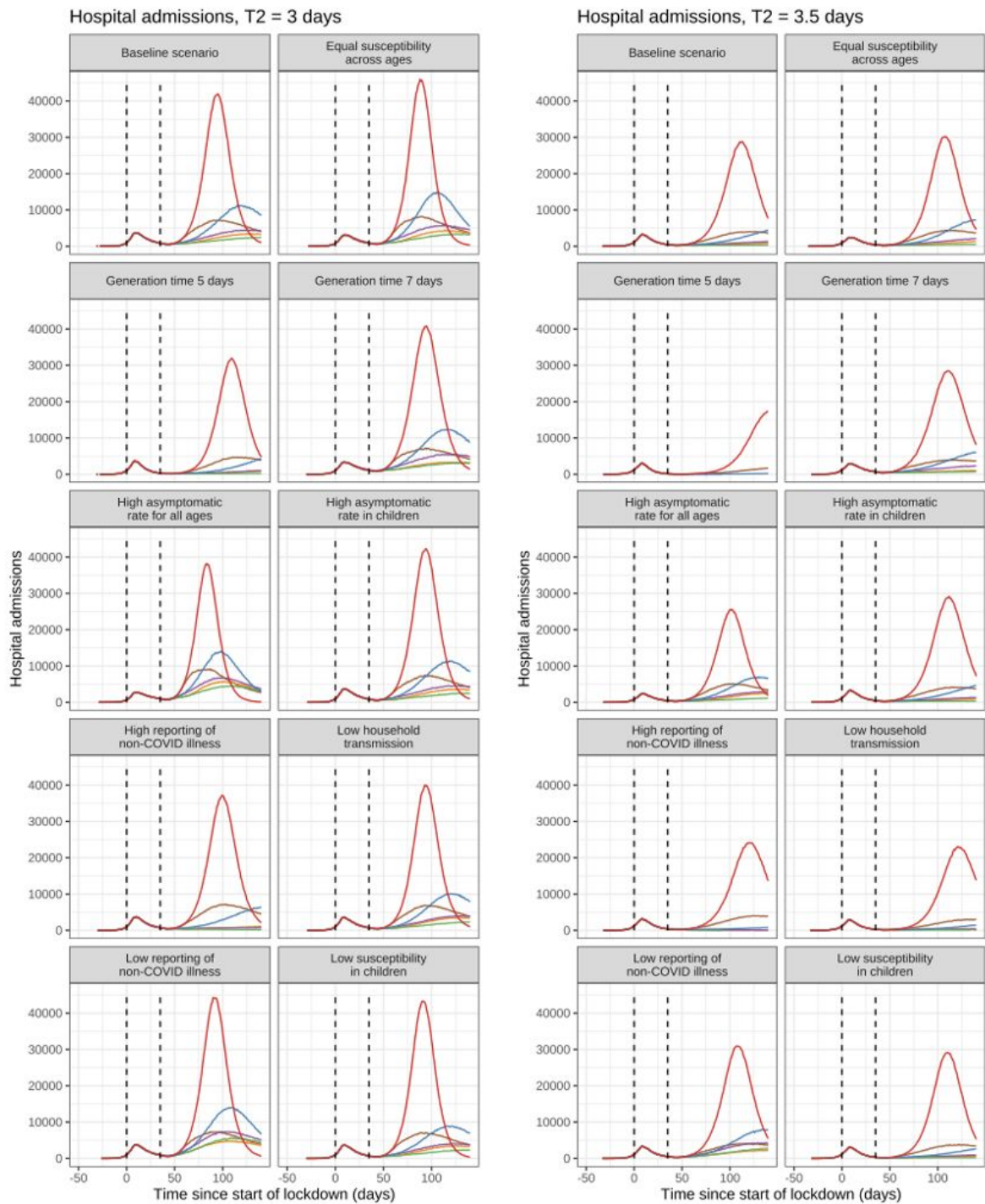
Supplementary Figure 2B: Individuals in hospital

Individuals in hospital, T2 = 3 days

Individuals in hospital, T2 = 3.5 days

Legend:
- 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
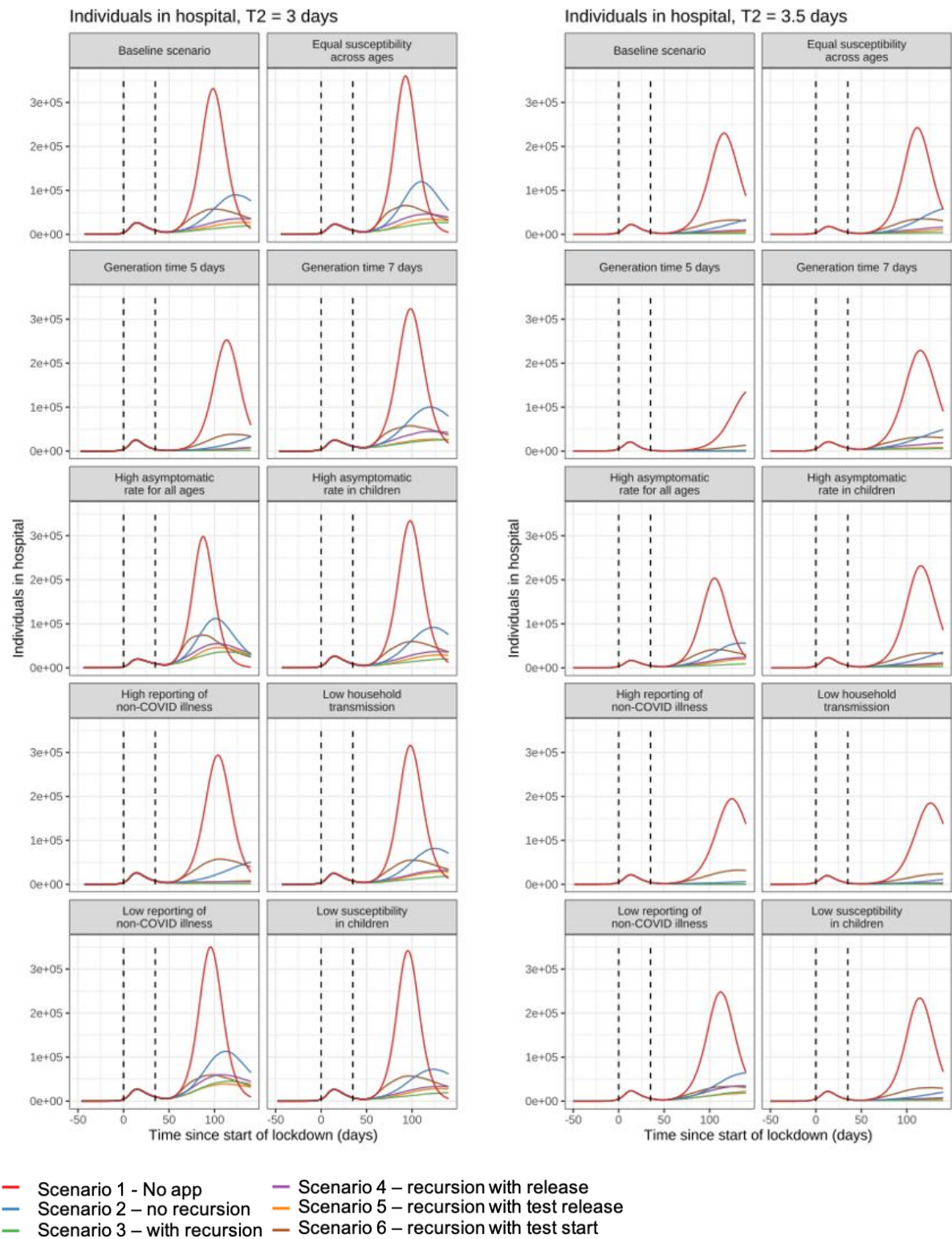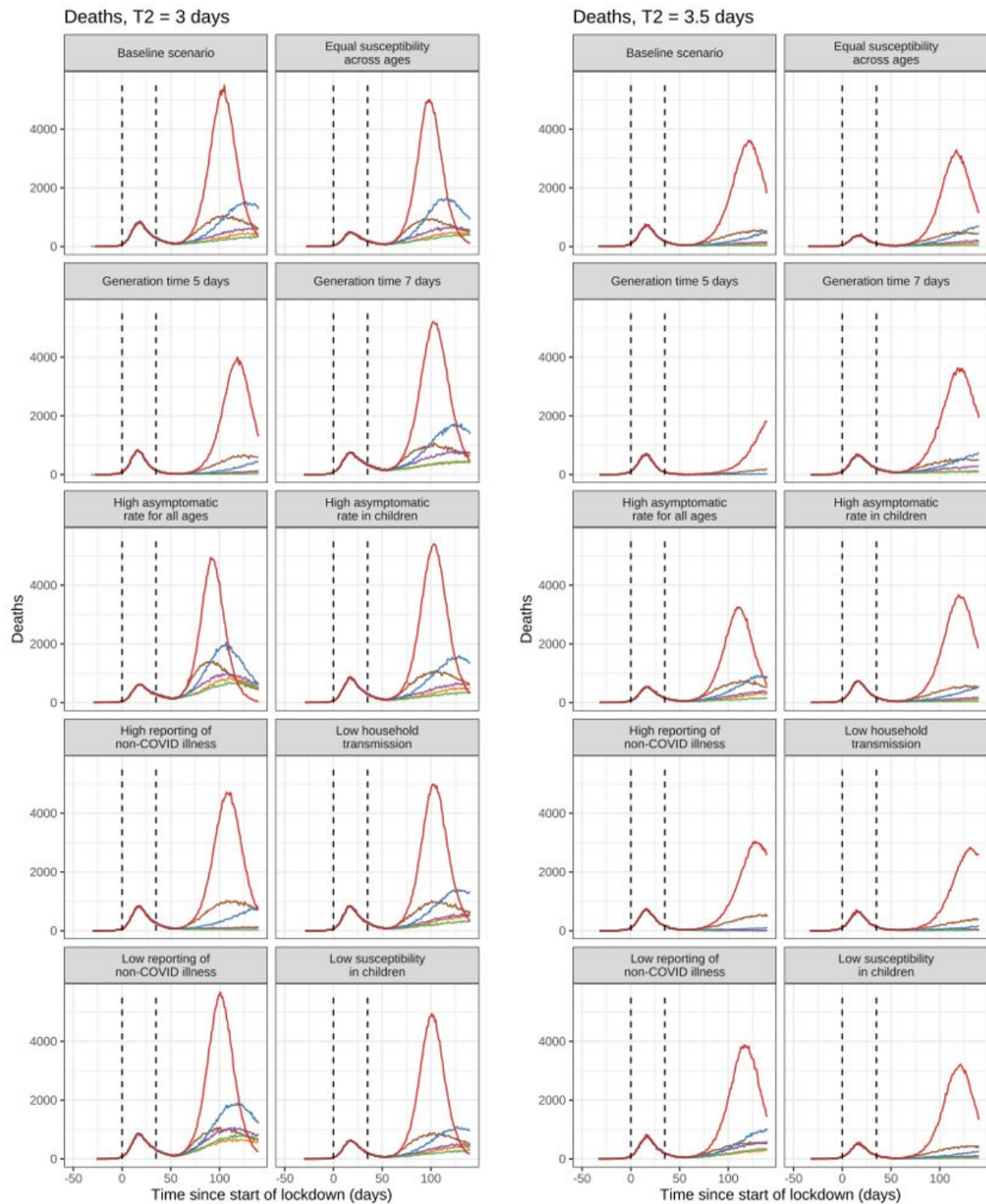
Supplementary Figure 3A: ICU admissions.
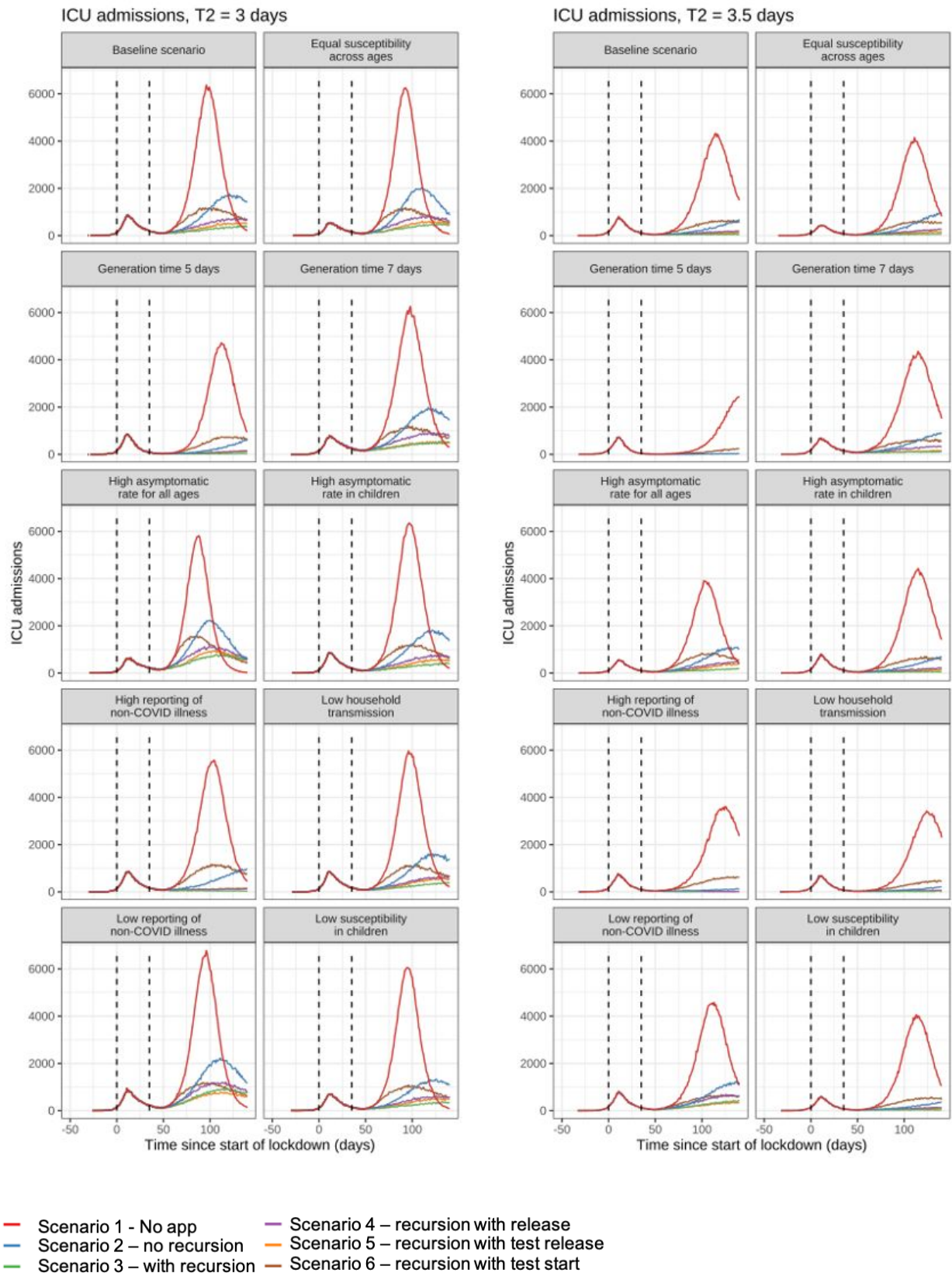
Supplementary Figure 3B: People in ICU
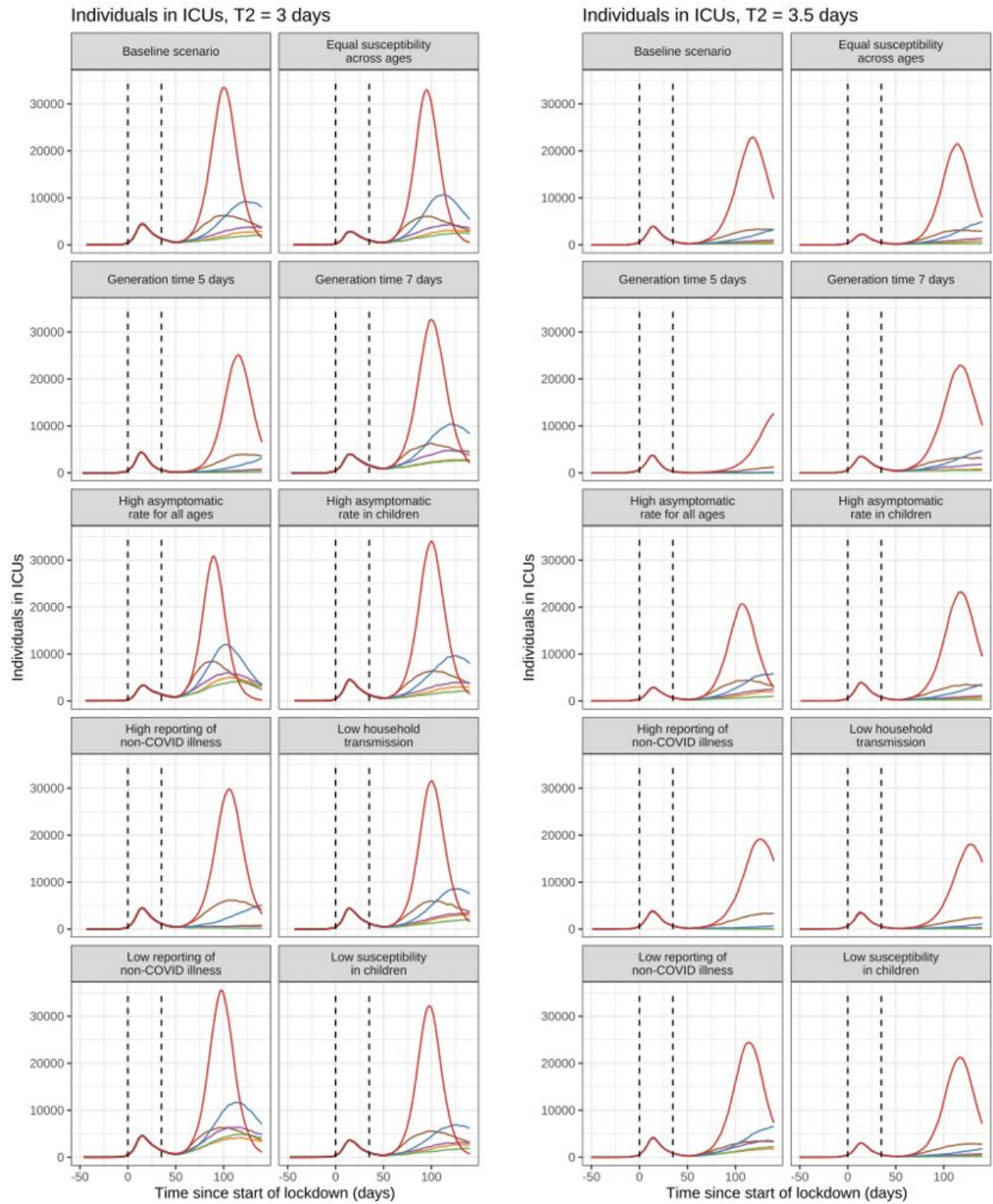
Scenario 1 - No app
Scenario 2 – no recursion
Scenario 3 – with recursion
Scenario 4 – recursion with release
Scenario 5 – recursion with test release
Scenario 6 – recursion with test start

Supplementary Figure 4: Daily deaths.

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

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