

# Can the app contain the spread? An agent-based model of COVID-19 and the effectiveness of smartphone-based contact tracing

Jonatan Almagor

MRC/CSO University of Glasgow Social and Public health science unit

Stefano Picascia (✉ [stefano.picascia@glasgow.ac.uk](mailto:stefano.picascia@glasgow.ac.uk))

MRC/CSO University of Glasgow Social and Public health science unit

---

## Research Article

**Keywords:** covid19, agent-based model, contact-tracing, smartphone

**Posted Date:** July 29th, 2020

**DOI:** <https://doi.org/10.21203/rs.3.rs-49802/v1>

**License:**  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

---

# Abstract

A contact-tracing strategy has been deemed necessary to contain the spread of COVID-19 following the relaxation of lockdown measures. Using an agent-based model, we explore one of the technology-based strategies proposed, a contact-tracing smartphone app. The model simulates the spread of COVID-19 in a population of agents on an urban scale. Agents are heterogeneous in their characteristics and are linked in a multi-layered network representing the social structure - including households, friendships, employment and schools.

We explore the interplay of various adoption rates of the contact-tracing app, different levels of testing capacity, and behavioural factors, to assess the ability of this track-and-trace strategy to mitigate the epidemic. Results suggest that the app can contribute substantially to the reduction of infections in the population, although complete suppression of the virus is unlikely to be achieved. The model also shows that, while adopting the app is beneficial for epidemic control in most cases, a high adoption rate is likely to generate an extensive increase in the demand for testing, which, if not met with adequate supply, may render the app counterproductive. This points to the crucial role of an efficient testing policy and the necessity to upscale testing capacity.

## Introduction

At the time of writing Coronavirus Disease 2019 (COVID-19) has caused just over 600,000 confirmed deaths in 216 countries worldwide<sup>1</sup>. In the absence of an effective treatment, let alone a vaccine, the only possible mitigation strategies are non-pharmaceutical<sup>2</sup>. In the initial phase of the pandemic lockdown measures, implemented with various degrees of firmness in most countries, have proven effective in containing the epidemic<sup>3</sup> and reducing the basic reproduction number  $R_0$  to less than 1. However, these measures cannot be sustained for a prolonged period of time, as the economic damage inflicted on workers, enterprises and governments would be irreparable. Therefore, a second phase of containment has followed, in which lockdown measures are lifted and different mitigation strategies are required, namely case isolation, tracking and contact-tracing, which are rooted in the established epidemiological toolkit<sup>4</sup>. These are particularly crucial in the context of a disease that is transmitted by a large proportion of a-symptomatic and pre-symptomatic individuals, as studies of early outbreaks in China and Italy have indicated<sup>5–8</sup>. However, manual contact tracing can be a time-consuming and inefficient exercise, since models show that the probability of epidemic control decreases rapidly when not enough cases are ascertained via contact-tracing before the onset of symptoms<sup>9</sup>. Technology-based solutions have been proposed to automatise the tracking process, in the form of contact tracing smartphone apps. Exploiting the Bluetooth Low Energy technology, these applications can trace other smartphones coming into close contact for a period of time compatible with potential infection transmission<sup>10</sup>. Once an individual who uses the app discovers having been infected, all smartphones who have come into close contact receive a notification, signalling the potential exposure. Intense debate followed in the scientific community and among the public on the risks, especially to privacy, and effectiveness of the app-based solution<sup>11</sup>. A number of studies, using a range of methodologies, tried to establish the optimal adoption rate and the

other necessary measures (such as social distancing and testing) required for the app to be effective in containing or suppressing the epidemic. Analytical mathematical models show a generally optimistic stance, suggesting that instantaneous contact tracing, such as that afforded by the app-based solution, can lead to epidemic control<sup>12</sup>, if at least 60% adoption rate of the app is attained<sup>13</sup>.

Alternatively, more complex models highlight possible unintended consequences of the mitigation strategies. For example, adopting the app with an inadequate number of tests available may lead to epidemic control, but at the price of an unrealistic number of people having to isolate<sup>14</sup>. Another model<sup>15</sup>, still in the development phase, seems to suggest that the app might not be effective at all, and other measures could be preferable, such as a random testing policy.

Here we present an agent-based model designed to explore the effectiveness of the app in containing or suppressing the epidemic. The model simulates the complex interplay between: (1) the portion of the population that uses the app, (2) the availability of testing, and (3) crucial behavioural factors, such as the willingness to comply with self-isolation instructions. The model explicitly simulates realistic interactions and examines the different policy options on the table. Our modelling approach tries to balance the competing needs for flexibility and scalability, while retaining as much complexity and descriptiveness as possible.

## Methods

### An agent-based model of COVID-19 transmission and mitigations

Modelling the effectiveness of mitigation strategies requires that we simulate them in parallel with the spread of the disease itself. Building on the principles of the SEIR approach, an agent-based model (ABM) was developed, simulating the spread of COVID-19 within the population of an urban area (full source code at <http://github.com/harrykipper/covid>). Since the virus is transmitted through contacts between infected and susceptible individuals, in order to understand the dynamics of the spread it is essential to represent the multiple social networks that connect individuals within a population and determine patterns of contacts. A major weakness of traditional compartmental infection models is their aggregated nature. The models divide the population into homogenous groups (compartments) in accordance with the state of the disease (SEIR); and disease transmission dynamics is assumed to occur as the infected group mixes with the susceptible group at certain rates<sup>16</sup>. These model assumptions do not account for the heterogeneity that exists between individuals within the groups, and simplifies the complexity of contact patterns in social networks that are important to understanding the course of an epidemic<sup>17</sup>. Our ABM intends to bridge this gap by modelling more realistic contact patterns that take place among heterogeneous agents interacting within a social network. Central to the agent-based approach is that each agent is represented in the model individually, with their specific characteristics (such as age and sex) and behaviour. Furthermore, interactions between agents are explicitly simulated. In the proposed model, agents are linked in a multi-layered social network that determines potential contacts. A contact is defined as an encounter between two agents where the virus may be transmitted.

The social network includes several types of social ties: household, relations, friends, workplace colleagues (for adults) and classmates (for school children). Contacts outside of the social network also take place and represent everyday “random” encounters with strangers in public places. In addition, a proportion of the working age population is assumed to work in customer-facing employment, which entails additional random contacts.

## Agents and social networks

We generate a synthetic population of circa 103,000 agents, derived from the 2011 UK Census<sup>18</sup>, including household type, gender and age within geographical zones (Detailed Characteristic Sector 2011). The population represents the city of Glasgow, Scotland. A multi-layered social network links agents within the following social structures:

- A *household* structure is created as follows: individuals who belong to households classed with the same type in the Census, and reside in the same locale, are linked together on the basis of age difference; single people below the age of 20 are assumed to live at home with one or two parents and siblings. Single people above the age of 20 are assumed to live independently, with a certain proportion co-habiting. Links of type ‘household’ are built among these
- Family *relatives* who don’t live in the same household (i.e. grandparents) are linked
- Several *workplace* sites are created, based on the distribution of workplace sizes in the city of Glasgow<sup>19</sup>. Active working-age agents are distributed among workplaces and linked to all co-workers at the same site as well as to a subset of colleagues who are assumed to be in closer, more frequent contact. Out of the working-age population, 13% of agents are assigned to customer-facing employment<sup>20</sup>, experiencing frequent contact with random agents of the population during work.
- A *friendship* network links agents over 14 years of age, generated following the Barabasi-Albert model<sup>21</sup> so that a scale-free network is produced, characterised by variation in number of friends per agent, with a median of 14 friends per agent, skewed towards similar
- Children between 6-17 years of age also belong to *classes* of maximum 30 children of the same age from the same zone and are linked together as

The subset of network contacts that an agent meets on a given day are determined based on the frequency of encounters and the number of contacts per encounter that characterise each type of social network (Table 1). For example, we assume that agents meet their household members every day and have contact with all of them, whereas they meet other relatives only twice a week, each time having contact with only one of them.

Type of contact	Frequency of encounters	No. of contacts per encounter	Transmission probability ( $\beta$ ) per contact
Household	Daily	All household members	$\beta$
School	5 days per week	50% of the class	$\beta \times 0.5$
Friendship / Acquaintance	Daily (age < 65 years) 2.5 days per week (age > 65 years)	1-10% of their friends	$\beta$
Relations	2 days per week	One relative per household	$\beta$
Workplace	5 days per week	All close colleagues and one from other colleagues	$\beta$
Workplace (public facing)	5 days per week	Random contacts are drawn from a Poisson distribution $Pois(\lambda)$ $\lambda = 1.5\% \times zone\_population$	$\beta \times 0.1$
Random	Daily (age < 65 years); 2.5 days per week (age > 65 years)	Random contacts are drawn from a Poisson distribution $Pois(\lambda)$ $\lambda = 0.5\% \times zone\_population$	$\beta \times 0.1$

**Table 1.** Contact type and transmission probability for social network based and random encounters

## Viral transmission

During each simulated day, all infected agents come into contact with a subset of agents from their social network and with a proportion of the population residing in their area (as defined in Table 1). For each contact with a susceptible agent the virus may be transmitted with a certain probability (Table 1). The probability of transmission during a contact with an agent in the network ( $\beta$ ) is higher than during a random contact with a stranger ( $0.1 \beta$ ), as we assume that a contact with a stranger is of shorter duration and reduced closeness, translating in a reduced likelihood of transmission (Table 1). In accordance with evidence that children are less susceptible to COVID-19<sup>22</sup>, we reduce the probability of infection by 50% for agents under the age of 16.

## Progression of the disease

Once a susceptible agent is infected, she progresses through the various states of the disease (Figure 1). The progression between disease states and the duration of each state are based on probabilities and durations which are age and gender dependent, as estimated in recent research on COVID-19 patients (Supplementary Table S1). Initially, the disease is in the incubation phase, a stage in which the agent is not infectious. A fraction of the infected agents becomes infectious 1-3 days before the end of the incubation period (pre-symptomatic infection), while others are infectious only at the end of incubation<sup>6, 23, 24</sup>. To reflect that, during each of the last 3 days of incubation agents have a 25% probability of becoming infectious. Following the incubation period, agents are either asymptomatic or symptomatic. Asymptomatic agents are able to infect others, but do not feel symptoms, and we assume that after the 3rd day of being infectious, infectiousness declines by 10% each day that follows<sup>25</sup>. Symptomatic

agents with a mild disease are assumed to feel the symptoms, but do not require hospitalisation; severely ill symptomatic agents initially stay at home and are then admitted to the hospital. Once severely ill agents are admitted to the hospital, we assumed they do not come into contact with any other agent. The model does not simulate nosocomial infection and always assumes the availability of hospital beds. In accordance with findings, agents stop infecting others after 7-11 days from the onset of symptoms.<sup>26</sup>

## Mitigation strategies: testing, contact tracing app

The model includes two types of mitigation tools to track and trace infected agents: the contact tracing app (CTA) and COVID-19 detection tests. The CTA is distributed among a fraction of the population aged over 14 years old. It stores in memory the ID of all other CTAs it came into contact with over the course of the previous 10 days. Infected agents who are aware of their illness (by either feeling symptoms or following a positive test) can use the CTA to notify their contacts of possible exposure. Tests are administered between 1 and 3 days after the onset of symptoms in an agent, and results are assumed to be determined within a day. We assume that a fixed number of tests are available; as agents are tested the stocks decrease and restocking takes place daily. Agents seek testing when: (a) they feel symptoms, (b) they are notified of possible exposure by the CTA or directly by an infected relative. We assume that over the course of any given week, 3.5% of the population has contracted influenza<sup>27</sup>, of which 30% will seek COVID-19 testing. These agents test negative and contribute to the depletion of tests.

## Agents' compliance to self-isolation

When agents self-isolate all their social ties are removed, except for household ties, as they are assumed to self-isolate at home. However, it is likely that some precautions are put in place between the infected and her household members; therefore, we assume a 30% reduction in the probability of transmission.

Without the certainty that testing provides, surveys suggest that not all agents will comply with self-isolation guidelines, both when feeling symptoms or when notified by the CTA<sup>28</sup>. We denote a parameter  $\omega_i$  representing the probability of agent  $i$  to self-isolate when feeling symptoms of COVID-19. We also assume that agents who are notified by the CTA, but do not feel any symptoms, are less likely to self-isolate (than if they had symptoms) without testing. Therefore, their probability to

self-isolate is reduced by factor  $\Omega$ , where  $0 < \Omega < 1$ . In the model, the probability of self-isolation varies between agents with mean  $\omega = 70\%$ . Figure 2 presents the algorithm triggered once an agent becomes aware of her symptoms. The procedure

triggers a chain of actions performed by symptomatic agents that involves testing (if available), decision to self-isolate and notifying relatives and CTA contacts. Following that, exposed agents who were notified performs similar actions.

# Model calibration and baseline scenario

The initial scenario reproduces a ‘business as usual’ situation with no mitigation in place, with contact frequencies as specified in Table 1. To verify the contact patterns generated by the ABM, we compared the properties of the distribution of agents’ daily contacts generated by the model to a distribution of contacts derived from a survey conducted in the UK<sup>29</sup>. Like the survey results, the distribution is characterized by a lognormal body and a power-law tail with an exponent of -2.1 (Figure 3a). The median and mean number of daily contacts are 17 and 12, respectively.

To calibrate the model, we tested a range of transmission probability ( $\beta$ ) values to generate the basic reproduction number of  $R_0$  2.8 in the initial three weeks of the epidemic, as estimated for the UK<sup>30</sup>. The best fit was achieved for  $\beta = 0.08$ .

After establishing the initial scenario, we simulate the post-lockdown situation expected in several countries, in which most restrictions are lifted but citizens are still encouraged to work from home when possible, limit social interactions, maintain physical distancing and wear face masks in public. Therefore, in this scenario we assume 3 days attendance per week at workplaces and schools; and a reduction of 30% in contacts in schools, with strangers, as well as the frequency of social meetings (within the ‘friendship’ network). In addition,  $\beta$  is reduced by 30% to reflect measures such as face mask usage, social distancing and increased hygiene, all of which reduce the likelihood of viral transmission. We refer to this situation as our *baseline* scenario. The reproduction number in this scenario comes down to 1.5. Comparing the scenarios, when social distancing is practised, the proportion of infected agents at the peak of the epidemic is significantly reduced from 34% to 10% (Fig 3c). The distribution of the sources of infection also varies, as the proportion of infection originating in workplaces and schools is reduced and the household becomes the predominant locus of transmission (Figure 3b).

## Experimental design

The core of our study explores the introduction of the CTA and the availability of testing into the baseline scenario of social distancing. We simulate the impact on viral spread of various combinations of: (1) proportion of CTA users in the population; (2) levels of testing capacity; (3) levels of compliance with self-isolation on the part of CTA users; (4) testing Table 2 summarises the parameter combinations explored in the model. Overall, we simulated 140 scenarios, each repeated 20 times to account for uncertainty in the results due to the stochasticity embedded in the model.

## Results

### Effectiveness of smartphone-based track-and-trace policies

To evaluate differences in viral diffusion under alternative parameter combinations, for each simulated scenario we plot the overall proportion of the population infected at the peak and throughout the whole course of the epidemic. We use the baseline scenario of no tests and no app as point of reference to better understand the impact of the mitigations that are introduced.

## Testing without tracing

When testing is the only mitigation used (with no CTA), as testing capacity increases from 0 to 3%, overall infections decreases from 52% to 42% (Figure 4) and infections at the peak are reduced by 41% (Figure 5). A further increase in testing capacity above 3% does not result in a further decrease in infections. This can be explained by the number of infected agents per day, which reaches 6% of the population at the peak of the epidemic (Figure 6a, light green line). Since around 50% of the infected are symptomatic, a testing capacity of 3% is sufficient. Thus, testing increases compliance with self-isolation which in turn reduces transmission.

## Introducing the CTA with a testing policy that prioritises symptomatic cases

Once the CTA is introduced, CTA users who are notified of having been in contact with an infected agent seek testing. When symptomatic agents are prioritised for testing, as the proportion of CTA users increases, overall infections throughout the epidemic decrease (Figure 4a-4b), and so do infections at the peak of the epidemic (Figure 5a-5b), irrespective of testing capacity. Moreover, a synergy exists between testing and the CTA, resulting in a larger reduction in the spread of the virus, reflected in a decrease in infections both overall, and at the peak of the epidemic.

Parameter	Value in experiments	Description
CTA users	0, 20, 40, 60, 80	% ***** over age 14 using CTA
Testing capacity	0, 0.5, 1, 1.5, 3, 6, <i>unlimited</i>	***** % of population that *** be tested per **** (reflective of UK policy announcements of 200,000 tests per day, corresponding to 2% of the population *** week)
***** of *** users	Low compliance: $\Omega = 0.5$ High compliance: $\Omega = 0.9$	Probability to self-***** for CTA user without testing decreases by $\Omega$ : ***** to self-isolate $= \omega_j * \Omega$
***** policy	a. Priority to symptomatic agents b. No priority	a. Each day ***** agents are tested, only **** CTA users b. Agents are tested on basis of first come ***** tested
Initial conditions	7% recovered from the virus; 300 (0.03%) agents infected	Reflects UK estimates ahead of lifting lockdown

**Table 2.** Parameters used in simulation experiments

As expected the decrease is substantial when testing is not limited: for example, when 80% of the population uses the CTA. In this case the percentage of the population infected throughout the epidemic decreases by half, from 52% to 26% (Figure 4a-4b) and cases at the peak of the epidemic reduce by 82% (Figure 5a-5b). Moreover, for intermediate levels of CTA adoption (40%-60%) and testing capacity (1.5%-3%), overall infections decrease to 32%-39% of the population and cases at the peak reduce by 45%-64%, depending on the scenario (Figure 4a-4b & Figure 5a-5b).

## **CTA with no priority to test symptomatic cases**

When the testing capacity is restricted and symptomatic agents are not prioritised for testing, an increase in the proportion of CTA users does not always lead to a decrease in infections (Figure 4c, 4d). This is observed for instance for a testing capacity of 3%. In this case, CTA adoption rates of 20% - 60% produce no improvement, or can even result in more infections than the scenario with no CTA users, both for high and low compliance with the CTA. This somewhat counterintuitive effect is explained by an inefficient testing policy. If symptomatic agents are not prioritised, they are as likely to be tested as those notified by the app, the majority of which are not infected. However, the increased demand for testing generated by CTA users who receive notifications depletes the stocks and prevents several cases from being detected. This phenomenon is apparent when comparing the 'efficiency' of the two testing policies (Figure 6c, 6d). When symptomatics are prioritised the proportion of positive tests is higher for any given rate of CTA adoption.

In general, adoption of the CTA triggers two competing dynamics. On one hand, it informs agents and leads some of those infected to isolate even in the absence of a test: a crucial outcome, given the high proportion of a-symptomatic cases. On the other hand, it leads to a large and somewhat 'inefficient' depletion of tests, as several uninfected agents would likely seek testing after a notification from the app. The model shows that this counterproductive effect can be mitigated either with a testing policy that prioritises symptomatics, or with an overall increase in testing capacity.

## **CTA users' compliance with self-isolation**

When compliance level with self-isolation of CTA users is high, overall infections throughout the epidemic are ~10% lower than when compliance level is low. The level of compliance with self-isolation becomes more influential the higher the proportion of CTA users, and at lower levels of testing capacity (Figure 4). E.g. in a scenario with no testing and 80% CTA users, overall infections reach 40% when compliance is high and 43% when compliance is low. The peak of the epidemic compared to baseline scenario is reduced by ~ 50% when compliance is high and ~40% when compliance is low (25% difference) (Figure 5).

## Discussion

The primary aim of this work is to contribute to the understanding of the complexity embedded in the interaction between the circulation of COVID-19 and the mitigations proposed. The results presented above show that app-based contact-tracing has the potential to mitigate the spread of COVID-19 in a social distancing scenario. With that, CTA efficiency in reducing the spread relies on additional elements: testing capacity and management of limited testing resources. When priority for testing is given to symptomatic cases the impact of CTA is linear; the higher the levels of CTA adoption, the more the virus is suppressed. This is true for any level of CTA adoption and any level of testing capability.

A more complex dynamic emerges in the model under limited testing resources when symptomatic cases are not prioritised. Increases in the adoption of the CTA produce a spillover effect whereby the large number of (mostly non-infected) agents notified by the CTA deplete the testing stock and prevent a number of symptomatic agents from being tested. In this case, the CTA may even produce an increase in the infection rate, especially if testing capacity is not sufficiently high relative to the number of app users.

These phenomena that emerge in the simulation can offer generalisable policy-relevant insights. First, the model shows that to optimise the contribution of the CTA towards epidemic control an adequate testing capacity has to be in place. This capacity is dependent on the proportion of CTA users in the population. Second, the specific way in which testing resources are managed substantially affects the effectiveness of containment. The suggestion is that governments should implement the CTA in parallel with a substantial increase in testing capacity, and accurately plan the details of the testing policy, keeping in mind that the mere availability of the CTA substantially alters patterns of demand for testing.

One of the aims of the model was to explore the impact of certain behavioural factors: we have shown that, even under conditions of low compliance of CTA users towards self-isolation, a significant decrease in the spread of the virus is achieved. Moreover, compliance with self-isolation can be enhanced by increasing the availability of testing to provide more certainty to exposed individuals regarding their infection state. Recent findings suggest that providing people with assurances about their livelihoods, by means of financial compensation, will increase compliance with self-isolation.<sup>31</sup>

As we demonstrated, in the more optimistic scenarios overall infections throughout the course of the epidemic are reduced by half, compared to the baseline scenario. At the same time the model shows that the mitigations simulated - CTA, testing, social distancing - are unlikely to completely suppress the epidemic. However, even if the epidemic is not suppressed, the app-based contact-tracing strategy contributes significantly to lowering the epidemic peak, which is crucial for the functioning and manageability of the healthcare system until a vaccine and other pharmaceutical treatments are developed.

While this model simulates realistic quantities and generates outputs in the form of levels of infection and trajectories of epidemic curves, those outlined above should not be interpreted as precise predictions. A limitation to the model's prediction capabilities are due to the unprecedented nature and novelty of

technology-based contact-tracing. Its outcomes may be influenced by additional behavioral and technological factors that are still to be explored and are not included in the current version of the model. These factors include the speed with which individuals will enact their decisions on whether to isolate, malfunction and inaccuracies in the operation of the app, and the processing speed and detection accuracy of the test.

In conclusion, we maintain that smartphone-based contact-tracing is a viable epidemic mitigation strategy, worth pursuing on the part of governments. We demonstrated that, as larger fractions of society adopt the CTA, the spread of the virus is increasingly reduced, and, therefore, the benefits extend to the wider population. In principle, the CTA offers speed and cost efficiencies that can complement and extend traditional manual contact-tracing methods. In our view, the idea of technology-based contact-tracing should not be dismissed, especially not on the grounds that it may widen inequality penalising those with limited access to the technology, or fail protect the elderly population who is less likely to adopt it. Paradoxically, users of the CTA do not benefit directly from doing so, since it only operates when an individual may already have been exposed to the virus<sup>32</sup>. While the CTA operates on a personal level by informing individuals of a possible risk of exposure, its general impact is at the societal level. By tracking exposed individuals and informing them to seek testing and self-isolate, transmission chains are interrupted, the spread of the virus is reduced, and so is the likelihood of infection for the whole population, including those who are not using the CTA.

## References

1. World Health Organization. Coronavirus disease pandemic (2020).
2. Ferguson, N. M. *et al.* Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Rep. March (2020). DOI: 10.25561/77482.
3. Flaxman, S., Mishra, S., Gandy, & Ai, E. Report 13: Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries. Tech. Rep. March (2020). DOI: 10.25561/77731.
4. Fraser, C., Riley, , Anderson, R. M. & Ferguson, N. M. Factors that make an infectious disease outbreak controllable. *Proc. Natl. Acad. Sci. United States Am.* **101**, 6146–6151, DOI: 10.1073/pnas.0307506101 (2004).
5. Lavezzo, *et al.* Suppression of COVID-19 outbreak in the municipality of Vo', Italy. *medRxiv* 1–23, DOI: 10.1101/2020.04.17.20053157 (2020).
6. Gandhi, , Yokoe, D. S. & Havlir, D. V. Asymptomatic Transmission, the Achilles' Heel of Current Strategies to Control Covid-19. *New Engl. J. Medicine* **382**, 2158–2160, DOI: 10.1056/NEJMe2009758 (2020).

7. Bai, *et al.* Presumed Asymptomatic Carrier Transmission of COVID-19. *JAMA* **323**, 1406, DOI: 10.1001/jama.2020.2565 (2020).
8. Tong, -D. *et al.* Potential Presymptomatic Transmission of SARS-CoV-2, Zhejiang Province, China, 2020. *Emerg. Infect. Dis.* **26**, 1052–1054, DOI: 10.3201/eid2605.200198 (2020).
9. Hellewell, J. *et al.* Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. *The Lancet Heal.* **8**, e488–e496, DOI: 10.1016/S2214-109X(20)30074-7 (2020).
10. Zastrow, Coronavirus contact-tracing apps: can they slow the spread of COVID-19? *Nature* DOI: 10.1038/ d41586-020-01514-2 (2020).
11. Sweeney, Tracking the debate on COVID-19 surveillance tools. *Nat. Mach. Intell.* **2**, 301–304, DOI: 10.1038/ s42256-020-0194-1 (2020).
12. Ferretti, L. *et al.* Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* **6936**, eabb6936, DOI: 10.1126/science.abb6936 (2020).
13. Fraser, C. *et al.* 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 Introduction 2 (2020).
14. Firth, J. A. *et al.* Combining fine-scale social contact data with epidemic modelling reveals interactions between contact tracing, quarantine, testing and physical distancing for controlling COVID-19. *medRxiv* 05.26.20113720, DOI: 10.1101/2020.05.26.20113720 (2020).
15. Assocc – agent-based social simulation of the coronavirus crisis (2020).
16. Chitnis, , Hyman, J. M. & Valle, S. Y. D. Mathematical models of contact patterns between age groups for predicting the spread of infectious diseases. *Math. Biosci. Eng.* **10**, 1475–1497, DOI: 10.3934/mbe.2013.10.1475 (2013).
17. Nielsen, B. , Sneppen, K., Simonsen, L. & Mathiesen, J. Heterogeneity is essential for contact tracing. *medRxiv* 2020.06.05.20123141, DOI: 10.1101/2020.06.05.20123141 (2020).
18. Office for National Statistics. 2011 uk census aggregate data, DOI: <http://dx.doi.org/10.5257/census/aggregate-2011-1> (2016).
19. Scottish Government. Statistics.gov.scot: Business, enterprise and energy (2019).
20. Office for National Statistics. Emp04: Employment by occupation (2018).
21. Barabási, A.-L. & Albert, R. Emergence of Scaling in Random Networks. *Science* **286**, 509–512, DOI: 1126/science. 286.5439.509 (1999).
22. Davies, N. G. *et al.* Age-dependent effects in the transmission and control of COVID-19 epidemics. *medRxiv* 2020.03.24.20043018, DOI: 10.1101/2020.03.24.20043018 (2020).
23. Lauer, S. A. *et al.* The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. *Annals Intern. Medicine* **172**, 577–582, DOI: 7326/M20-0504 (2020).

24. Huang, L. *et al.* Rapid asymptomatic transmission of COVID-19 during the incubation period demonstrating strong infectivity in a cluster of youngsters aged 16-23 years outside Wuhan and characteristics of young patients with COVID-19: A prospective contact-tracing study. *Infect.* **80**, e1–e13, DOI: 10.1016/j.jinf.2020.03.006 (2020).
25. Yang, , Gui, X. & Xiong, Y. Comparison of Clinical Characteristics of Patients with Asymptomatic vs Symptomatic Coronavirus Disease 2019 in Wuhan, China. *JAMA Netw. Open* **3**, e2010182, DOI: 10.1001/jamanetworkopen.2020.10182 (2020).
26. MIN, C. O. Position statement from the national centre for infectious diseases and the chapter of infectious disease physicians, academy of medicine, singapore: Period of infectivity to inform strategies for de-isolation for covid-19 patients (2020).
27. Public Health England. Flusurvey (2020).
28. Altmann, S. *et al.* Acceptability of App-Based Contact Tracing for COVID-19: Cross-Country Survey Evidence. *SSRN J.* 1–52, DOI: 10.2139/ssrn.3590505 (2020).
29. Danon, L., House, A., Read, J. M. & Keeling, M. J. Social encounter networks: collective properties and disease transmission. *J. The Royal Soc. Interface* **9**, 2826–2833, DOI: 10.1098/rsif.2012.0357 (2012).
30. Stedman, *et al.* A phased approach to unlocking during the COVID-19 pandemic—Lessons from trend analysis. *Int. J. Clin. Pract.* 1–7, DOI: 10.1111/ijcp.13528 (2020).
31. Bodas, & Peleg, K. Self-Isolation Compliance In The COVID-19 Era Influenced By Compensation: Findings From A Recent Survey In Israel. *Heal. affairs (Project Hope)* **39**, 936–941, DOI: 10.1377/hlthaff.2020.00382 (2020).
32. Rizzo, COVID-19 contact tracing apps: the "elderly paradox". *Public Heal.* **185**, 127, DOI: 10.1016/j.puhe.2020.06.045 (2020).

## Declarations

## Acknowledgements

This work was supported by the Medical Research Council [grant numbers MC\_UU\_12017/10 and MC\_UU\_12017/14] and Chief Scientist Office [grant number SPHSU10]. Both grants provide 5 years of core research support for JA and SP.

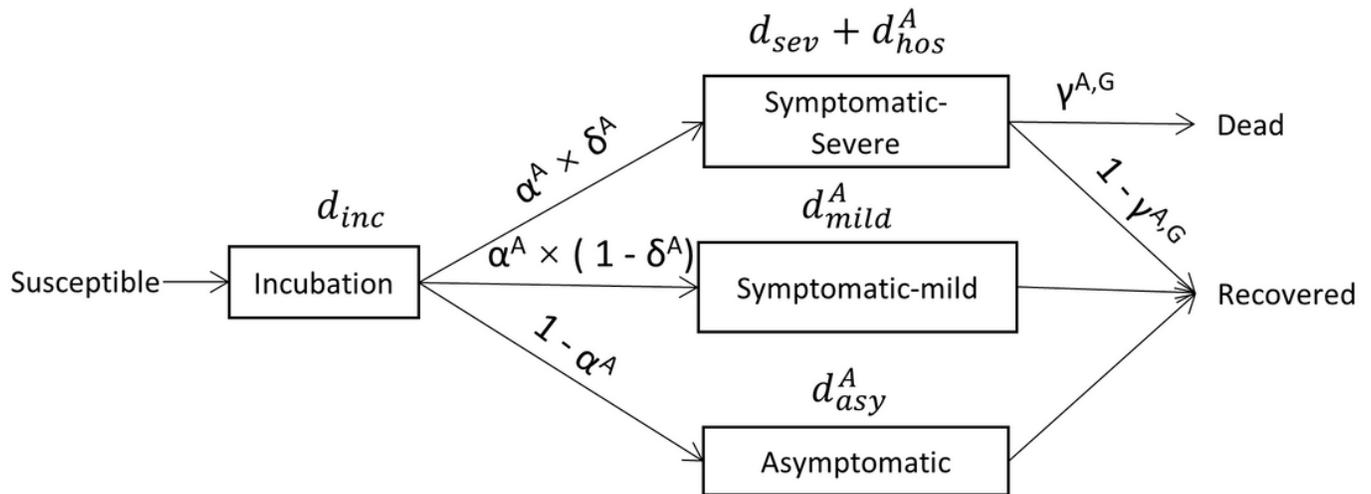
## Author contributions statement

Both authors conceived and programmed the model, designed experiments, analysed the results, and reviewed the manuscript.

# Additional information

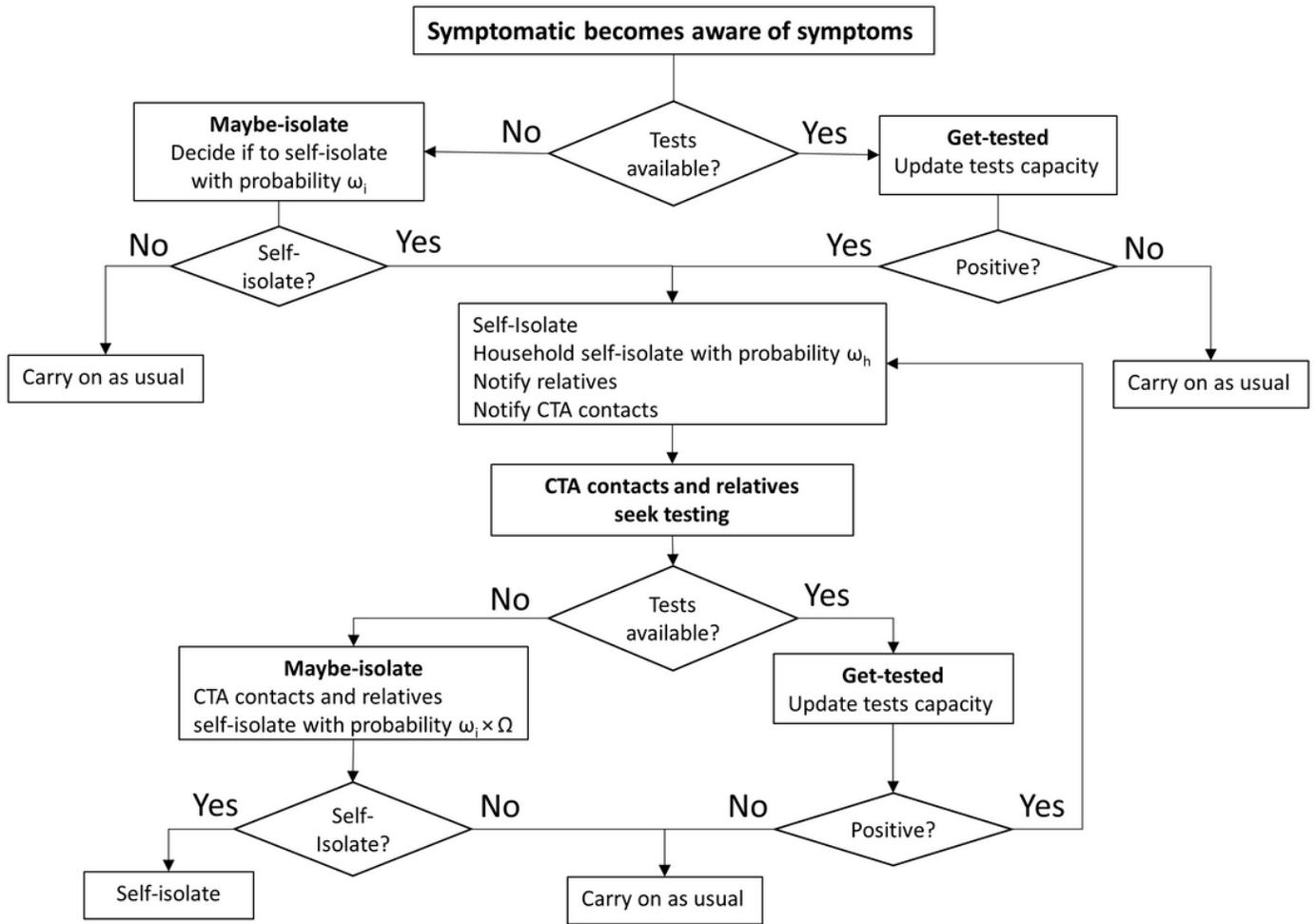
**Competing interests** (The authors declare no competing interests).

## Figures



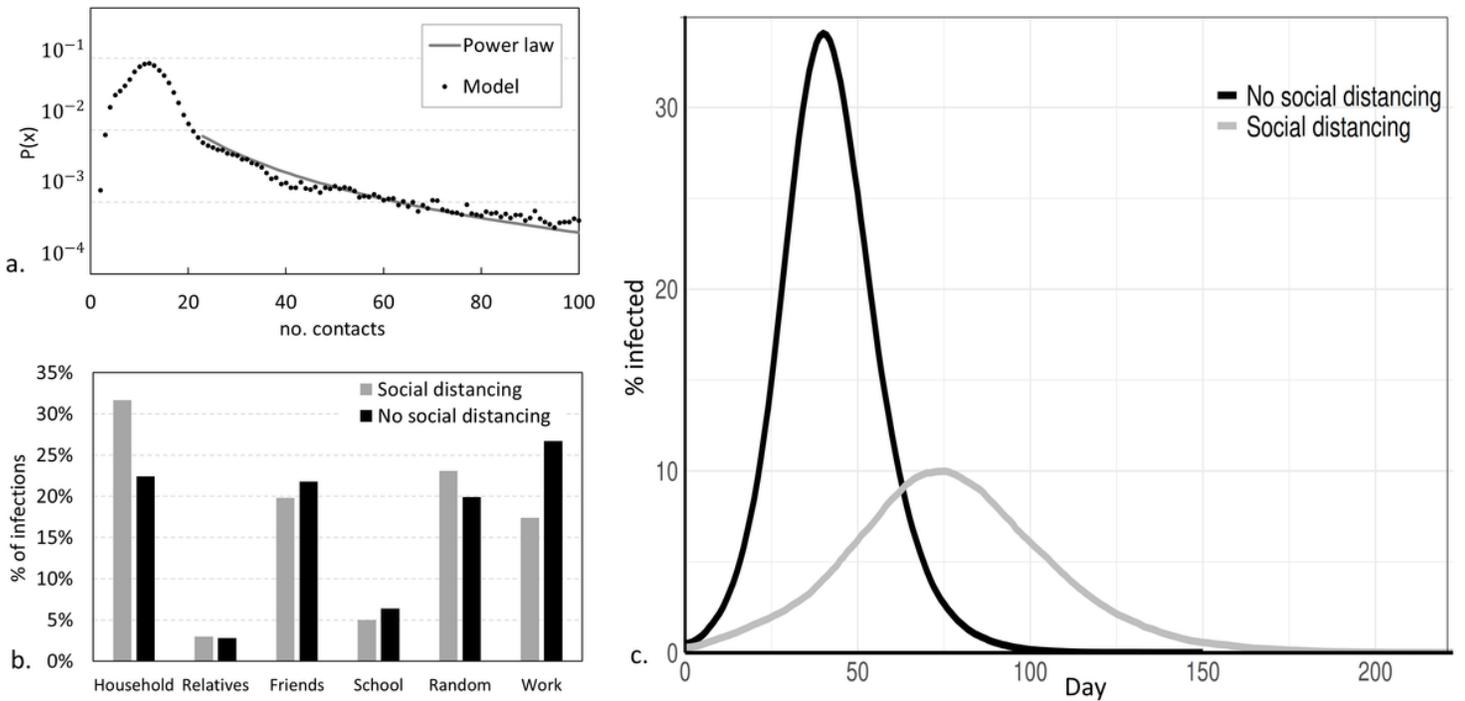
**Figure 1**

Disease progression. Rectangles represent states of the disease and arrows the transition between states.  $d^A$  denotes the duration of the disease state given the age  $A$  of the agent. Agents with severe symptomatic disease spend  $d_{sev}$  days at home before being admitted to the hospital for a duration of  $d_{hos}^A$  days. Transition between disease states occurs with age dependent probabilities; where  $\alpha^A$  and  $1 - \alpha^A$  denote the probability of an agent of age  $A$  being symptomatic and asymptomatic, respectively.  $\delta^A$  denotes the probability for a symptomatic agent to progress into severe disease;  $\gamma^{A,G}$  denotes the probability of a severely ill agent of age  $A$  and gender  $G$  to die. For details of parameter values see Supplementary table S1



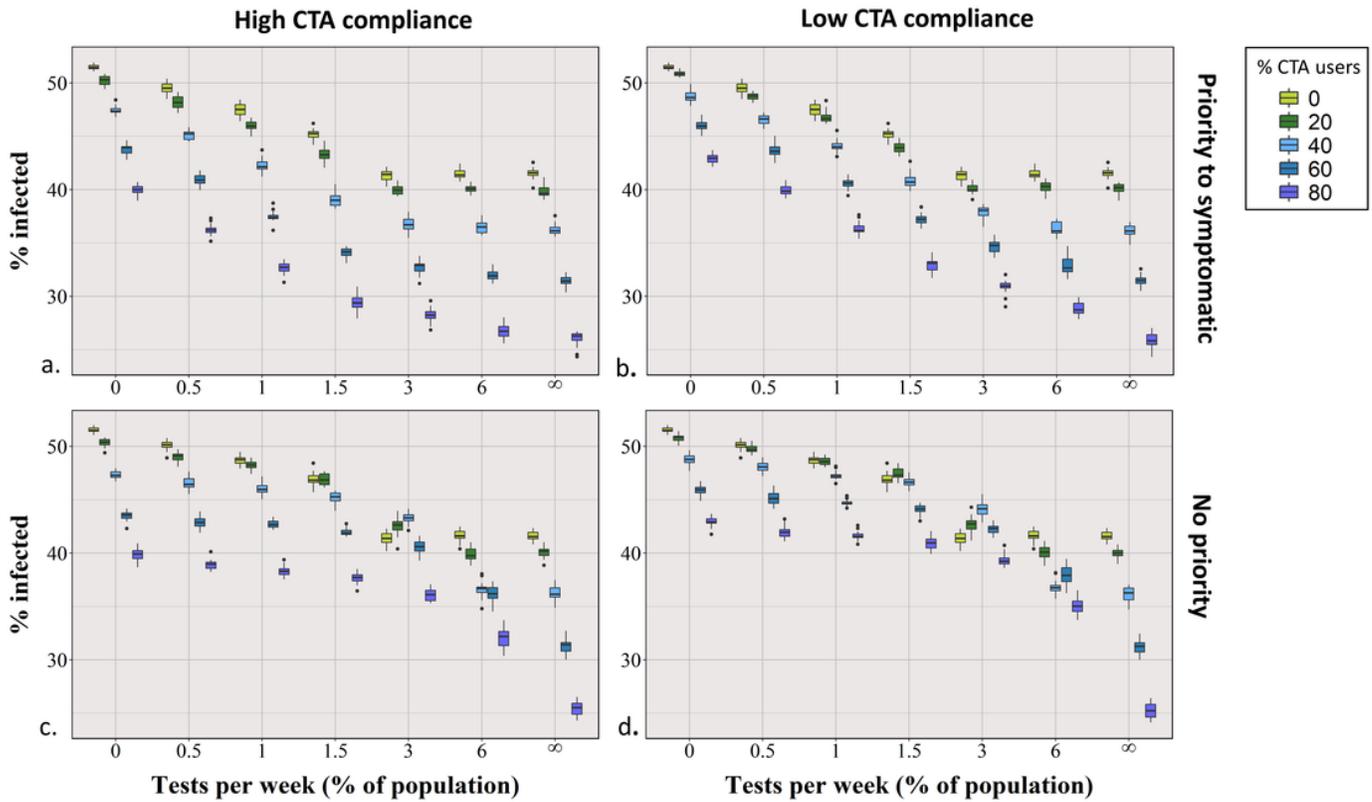
**Figure 2**

Procedure for testing and self-isolation and CTA notification. Once symptomatic agent  $i$  becomes aware of the disease, she seeks testing. If tests are available, she gets tested, receives a positive result and self-isolates. Household members  $h$  of agent  $i$  will also self-isolate with probability  $\omega_h$ . Agent  $i$  will notify her relatives that she is infected. If agent  $i$  uses the CTA all her contacts recorded in the previous 10 days are notified. When tests are unavailable, agent  $i$  will self-isolate with probability  $\omega_i$ . In case the agent chooses to self-isolate the aforementioned procedure of self-isolation will take place, otherwise he will continue as usual. Once CTA user  $j$  is notified, she seeks testing. If testing is unavailable, she may self-isolate with probability  $\omega_j * \Omega$



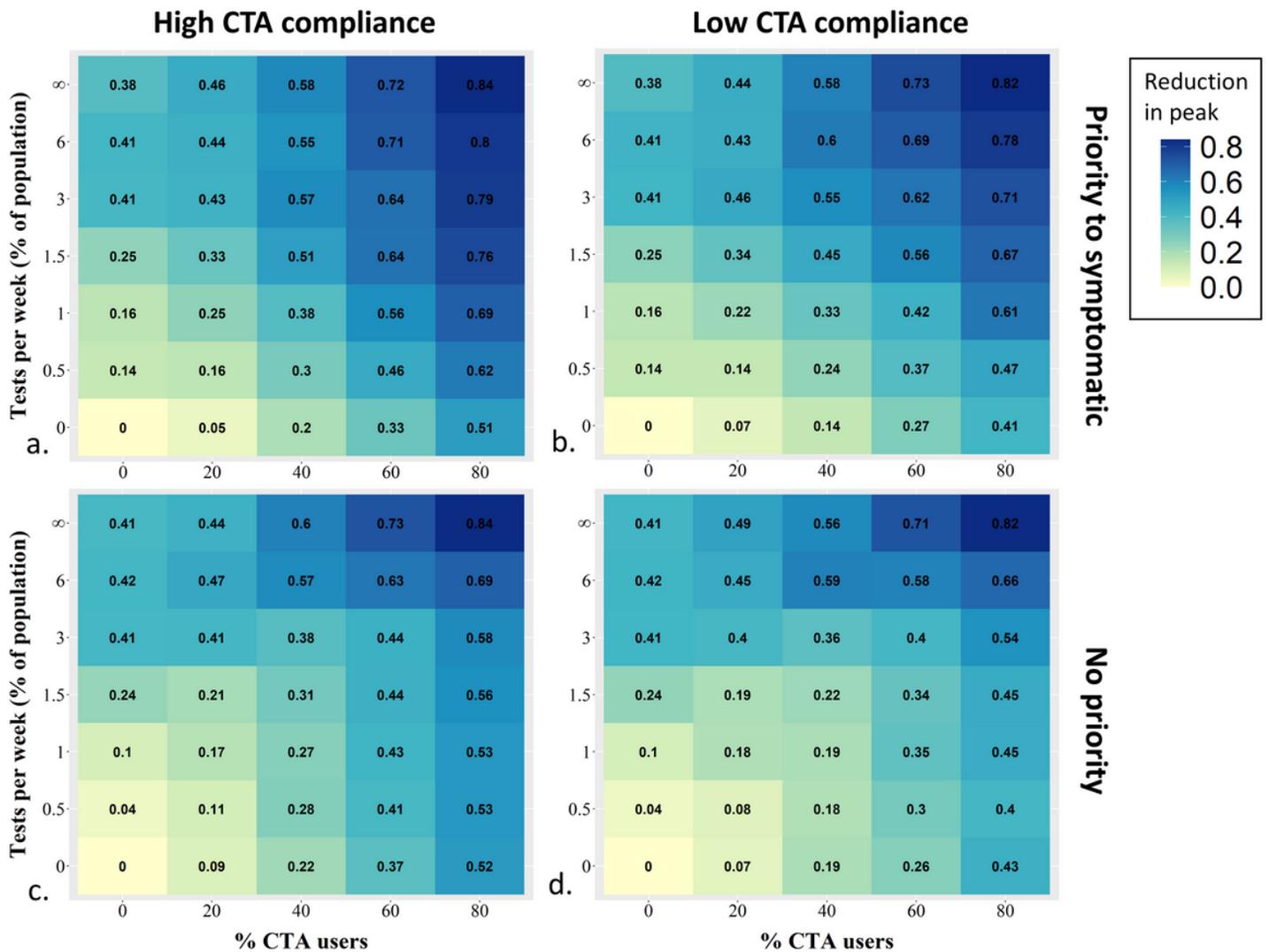
**Figure 3**

Distribution of daily contacts and epidemic dynamics with and without social distancing. (a) Distribution of number of daily contacts generated by the ABM (black dots) and power-law distribution (gray line) with an exponent of -2.1 as a reference for the shape of the distribution tail. (b) Distribution of infection sources by type of contact, with and without social distancing. (c) Percent infected by day, from beginning to end of the epidemic, with and without social distancing



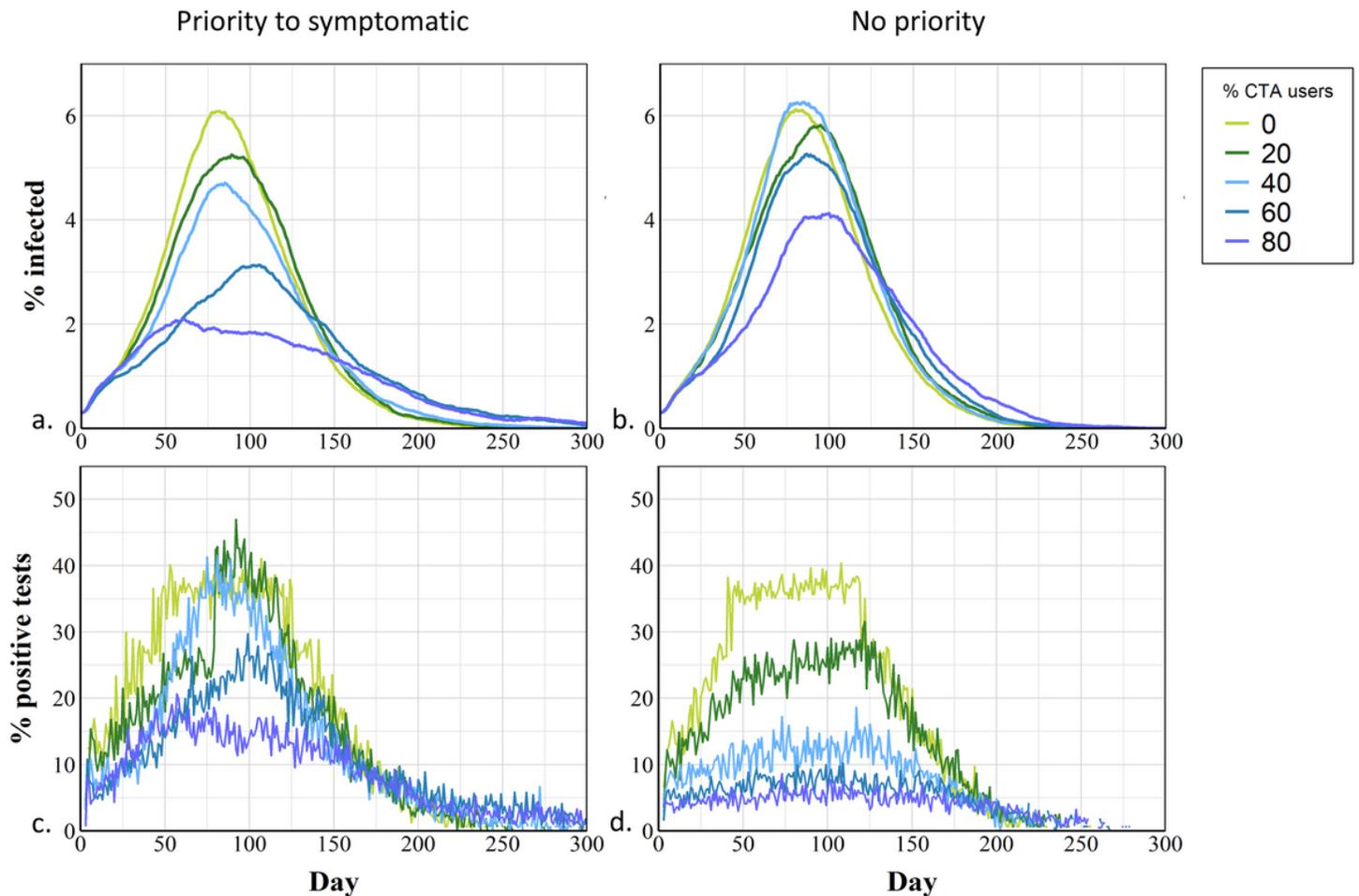
**Figure 4**

Percentage of the population infected during the course of epidemic. Scenarios vary by testing capacity (x-axis) and percentage of CTA users (Boxplot's color). Diagrams are organized by testing policy and compliance with self-isolation of CTA users: (a) High compliance and priority for testing symptomatic cases; (b) Low compliance and priority for testing symptomatic cases; (c) High compliance and no priority for testing symptomatic cases; (d) Low compliance and no priority for testing symptomatic cases. The boxplots show the median and interquartile range of multiple simulation runs.



**Figure 5**

Reduction in infected cases at the peak of the epidemic. Reduction is relative to the peak of the epidemic in the baseline scenario (10%) and measured as a fraction of this value. Scenarios vary by percent of CTA users (x-axis) and testing capacity (y-axis) and organised by testing policy and compliance with self-isolation of CTA users: (a) high compliance and priority for testing symptomatic cases; (b) low compliance and priority for testing symptomatic cases; (c) high compliance and no priority for testing symptomatic cases; (d) low compliance and no priority for testing symptomatic cases.



**Figure 6**

Infected cases and positive tests for a testing policy with and without priority to symptomatic cases. Percentage infected (a) and percentage of positive tests (c) by day, for a testing policy with priority to symptomatic. Percentage infected (b) and percentage positive tests (d) by day, for a testing policy without priority. Percentage of CTA users in the scenario is marked by line colour. In these scenarios: testing capacity = 3% and CTA compliance is high. Note that in the scenarios with no CTA users, although only symptomatic cases are tested, the percentage of positive tests is not 100% because of influenza cases that are also being tested.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [suppnat.pdf](#)