

# Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study

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## Summary

**Background** In countries with declining numbers of confirmed cases of COVID-19, lockdown measures are gradually being lifted. However, even if most physical distancing measures are continued, other public health measures will be needed to control the epidemic. Contact tracing via conventional methods or mobile app technology is central to control strategies during de-escalation of physical distancing. We aimed to identify key factors for a contact tracing strategy to be successful.

**Methods** We evaluated the impact of timeliness and completeness in various steps of a contact tracing strategy using a stochastic mathematical model with explicit time delays between time of infection and symptom onset, and between symptom onset, diagnosis by testing, and isolation (testing delay). The model also includes tracing of close contacts (eg, household members) and casual contacts, followed by testing regardless of symptoms and isolation if testing positive, with different tracing delays and coverages. We computed effective reproduction numbers of a contact tracing strategy ( $R_{\text{CTS}}$ ) for a population with physical distancing measures and various scenarios for isolation of index cases and tracing and quarantine of their contacts.

**Findings** For the most optimistic scenario (testing and tracing delays of 0 days and tracing coverage of 100%), and assuming that around 40% of transmissions occur before symptom onset, the model predicts that the estimated effective reproduction number of 1.2 (with physical distancing only) will be reduced to 0.8 (95% CI 0.7–0.9) by adding contact tracing. The model also shows that a similar reduction can be achieved when testing and tracing coverage is reduced to 80% ( $R_{\text{CTS}}$  0.8, 95% CI 0.7–1.0). A testing delay of more than 1 day requires the tracing delay to be at most 1 day or tracing coverage to be at least 80% to keep  $R_{\text{CTS}}$  below 1. With a testing delay of 3 days or longer, even the most efficient strategy cannot reach  $R_{\text{CTS}}$  values below 1. The effect of minimising tracing delay (eg, with app-based technology) declines with decreasing coverage of app use, but app-based tracing alone remains more effective than conventional tracing alone even with 20% coverage, reducing the reproduction number by 17.6% compared with 2.5%. The proportion of onward transmissions per index case that can be prevented depends on testing and tracing delays, and given a 0-day tracing delay, ranges from up to 79.9% with a 0-day testing delay to 41.8% with a 3-day testing delay and 4.9% with a 7-day testing delay.

**Interpretation** In our model, minimising testing delay had the largest impact on reducing onward transmissions. Optimising testing and tracing coverage and minimising tracing delays, for instance with app-based technology, further enhanced contact tracing effectiveness, with the potential to prevent up to 80% of all transmissions. Access to testing should therefore be optimised, and mobile app technology might reduce delays in the contact tracing process and optimise contact tracing coverage.

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## Introduction

Many countries are preparing so-called exit strategies from the COVID-19 lockdown while attempting to successfully control transmission. Contact tracing, in combination with the quarantine and potential testing of contacts, is considered a key component in a phase when lockdown measures are gradually lifted.<sup>1–8</sup> Contact tracing is an intervention where an index case with confirmed infection is asked to provide information about contact people who were at risk of acquiring infection from the index case within a given time period before the positive test result. These contacts are then traced and informed

about their risk, quarantined, and tested if eligible for testing according to national testing guidelines. This requires upscaling of conventional contact tracing capacity. The potential of mobile device apps to support contact tracing is widely discussed and such technology has been used in several countries such as South Korea and Taiwan. Although these countries have successfully reduced case numbers, no causal relationship between use of app technology and epidemic control has yet been shown.<sup>9–14</sup> Many uncertainties remain on the optimal process of contact tracing with conventional methods or mobile apps, on the timing of testing for current or past

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### Research in context

#### Evidence before this study

We searched PubMed, bioRxiv, and medRxiv for articles published in English from Jan 1 to June 20, 2020, with the following keywords: ("2019-nCoV" OR "novel coronavirus" OR "COVID-19" OR "SARS-CoV-2") AND "contact tracing" AND "model\*". Population-level modelling studies of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) have suggested that isolation and tracing alone might not be sufficient to control outbreaks and additional measures might be required. However, few studies have focused on the effects of lifting individual measures once the first wave of the epidemic has been controlled. Lifting measures must be accompanied by effective contact tracing strategies to keep the effective reproduction number below 1. A detailed analysis, with special emphasis on the effects of time delays in testing of index patients and tracing of contacts, has not been done.

#### Added value of this study

We did a systematic analysis of the various steps required in the process of testing and diagnosing an index case as well as tracing and isolating possible secondary cases of the index case. We then used a stochastic transmission model that distinguishes between close contacts (eg, household members) and casual contacts to assess which steps and (possible) delays are crucial in determining the effectiveness of a contact tracing strategy. We evaluated how

delays and the level of contact tracing coverage influence the effective reproduction number, and how fast contact tracing needs to be to keep the reproduction number below 1. We also analysed what proportion of onward transmission can be prevented with short testing and tracing delays and high contact tracing coverage. Assuming that around 40% of transmission occurs before symptom onset, we estimate that keeping the time between symptom onset and testing and isolation of an index case short (<3 days) is imperative for successful contact tracing. This implies that the process leading from symptom onset to receiving a positive test should be minimised by providing a sufficient number of easily accessible testing facilities. In addition, reducing contact tracing delays also helps to keep the reproduction number below 1.

#### Implications of all the available evidence

Our analyses highlight that a contact tracing strategy will only contribute to containment of COVID-19 if it can be organised such that delays in the process from symptom onset to isolation of the index case and their contacts are very short. The process of conventional contact tracing should be reviewed and streamlined, while mobile app technology might offer a tool for speeding up the process. Reducing delay in testing individuals for SARS-CoV-2 should be a key objective of a contact tracing strategy.

infection, and on the required coverage of contact tracing needed.

Modelling studies have shown how mobile apps can increase effectiveness of contact tracing compared with conventional approaches, but effectiveness depends on what proportion of the population will use the app consistently for a sufficiently long period of time.<sup>9</sup> Modelling studies have predicted that contact tracing alone cannot control an outbreak if tracing coverage is too low.<sup>2,15</sup> The tracing coverage needed depends on how much transmission occurs before symptom onset, and on the details of the tracing process.

In previous work, we have investigated the impact of timeliness and completeness of case reporting on the effectiveness of surveillance and interventions,<sup>16,17</sup> and we quantified the timeliness of contact tracing of infected passengers during an airline flight for the 2009 influenza pandemic.<sup>18</sup> In all of these studies, the timing of various steps in the monitoring and intervention chain emerged as a key factor for effectiveness of a public health response. Usually, there are identifiable delays in the response chain that might be crucial to the overall effectiveness of a strategy.

Here, we analyse in detail the process chain of identifying index cases by symptom reporting, testing of index cases, and subsequent contact tracing, with the aim to inform policy makers on the relative importance of key steps in the process. We use a mathematical model that reflects the various steps and delays in

the contact tracing process to quantify how delays affect the effective reproduction number and the fraction of onward transmission prevented per diagnosed index case.<sup>5,19</sup>

## Methods

### Time delays in contact tracing

Our starting point is an assumed effective reproduction number ( $R_e$ ) for COVID-19 of around 1, describing a situation with physical distancing but measures lifted to some extent. We then quantify the relative contribution of the individual components of a contact tracing strategy required to bring and maintain the effective reproduction number with contact tracing ( $R_{CTS}$ ) to a value below 1. For simplicity, we do not include transmission in health-care settings, because in settings such as nursing homes, which can be viewed as closed populations, other interventions might be more appropriate.

We break down the process of contact tracing into two steps (figure 1; appendix p 6). In the first step, an index case acquires the infection (at time  $T_0$ ), then after a short latent period becomes infectious (at time  $T_1$ ) and then possibly symptomatic (at time  $T_2$ ), which here is defined as being eligible for testing. Subsequently, a proportion of these symptomatic individuals, determined by the testing coverage, gets tested and diagnosed (at time  $T_3$ ). The time between  $T_2$  and  $T_3$  is called the testing delay ( $D_1 = T_3 - T_2$ ) and can vary between 0 and 7 days, and in this period individuals might self-quarantine. We define testing

See Online for appendix

coverage as the proportion of all symptomatic cases that are tested. After being diagnosed, we assume index cases are isolated with no further transmission.

The second step is tracing contacts of the index case, which occurs at time  $T_4$ . A fraction of those contacts, determined by the tracing coverage, will be found and tested. We assumed that all traced contacts do not transmit any further, either because they are tested and isolated if infected or because they are effectively quarantined. The effectiveness of these measures are therefore subsumed in the tracing coverage. The time between  $T_3$  and  $T_4$  is the tracing delay ( $D_2=T_4-T_3$ ), which can range from 0 days (eg, with app technology) to 3 days (with conventional approaches); this range was obtained through personal communications with public health professionals who are working with contact tracing in practice, as well as existing estimates for influenza.<sup>18</sup> In this step, tracing coverage is defined as the proportion of contacts detected, which either depends on the capacity of conventional approaches or on the fraction of the population using suitable app technology for screening.

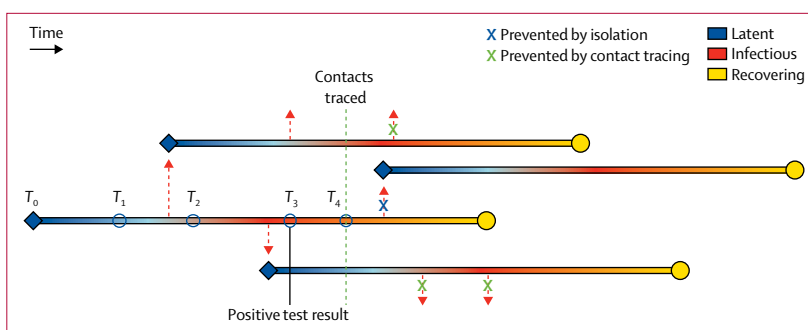
### Strategies considered

We considered two particular contact tracing strategies: conventional contact tracing and mobile app technology contact tracing (reproduction number  $R_{CTS}$ ). We did not consider hybrid approaches of combined conventional and mobile app-based strategies. We compared these strategies with a physical distancing strategy (reproduction number  $R_0$ ) and an isolation strategy where symptomatic individuals get tested and isolated without subsequent contact tracing (reproduction number  $R_{iso}$ ).

As 100% testing and tracing coverages are difficult to achieve, we defined a best-case scenario with 80% testing and tracing coverage, where people eligible for testing are immediately tested with a very fast test result (testing delay 0 days) and immediate isolation when testing positive. In contact tracing strategies, this is followed by immediate tracing of contacts (tracing delay 0 days), who immediately adhere to isolation measures. In our analyses, this best-case scenario can only be achieved by mobile app use. We consider more realistic scenarios where testing and tracing are suboptimal—eg, a conventional contact tracing strategy—and we vary these parameters separately in a sensitivity analysis (appendix pp 9–12).

### Effectiveness of contact tracing at the population level

To analyse the impact of delays in testing and tracing on the effectiveness of contact tracing strategies at the population level, we use a model introduced by Kretzschmar and colleagues,<sup>19</sup> which was adapted for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2).<sup>5</sup> The stochastic model describes an epidemic as a branching process with progression through latent infection and an infectious period in time steps of 1 day. Infectivity and probability of symptom onset per day of the infectious



**Figure 1: Schematic of the contact tracing process and its time delays**

$T_0$ =time of infection of index case.  $T_1$ =onset of infectiousness.  $T_2$ =symptom onset.  $T_3$ =time of positive diagnosis.  $T_4$ =time of tracing and quarantining of contacts.

period and numbers of contacts per day were fitted to distributions taken from published data.<sup>20–24</sup> With these distributions, around 40% of transmissions take place before symptom onset. We distinguish between close contacts (eg, household contacts) and casual contacts, which differ in the risk of acquiring infection from the index case. Contact definitions were based on those used in the Polymod study,<sup>23</sup> where a contact is defined as having a two-way conversation of three or more words in physical presence or having physical contact with another person. A high-risk contact is one that includes physical contact, lasts more than 15 min, or occurs on a regular basis. Additionally, the time required for tracing and isolating infected contacts and the coverage of tracing can differ between these types of contacts and between different types of contact tracing (eg, conventional vs mobile app supported). We assume that isolation is perfect—ie, that isolated people do not transmit any longer—and that all traced infected contacts are isolated, regardless of whether they develop symptoms or not. The model allows for explicit computation of the basic reproduction number  $R_0$ ,  $R_0$ ,  $R_{iso}$ , and  $R_{CTS}$ . Reproduction numbers were calculated as expectations, and distributions of individual reproduction numbers were simulated. The model was coded in Mathematica 12.1. Further details are presented in the appendix (pp 3–9).

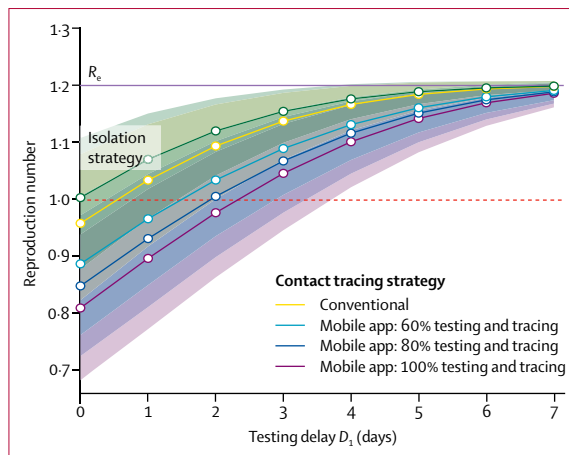
### Parameter settings

We assumed that without physical distancing, individuals have on average four close contacts and nine casual contacts per day, with stochastic variability. The distributions were fitted to data from the Polymod study for the Netherlands.<sup>23</sup> Transmission probability per contact for close contacts was taken to be four times higher than for casual contacts. We assumed that 80% of all infected people develop symptoms at some time during their infectious period and 20% remain asymptomatic. Symptomatic and asymptomatic cases were assumed to be equally infectious. Overall, the transmission probability was calibrated to  $R_0=2.5$ . For physical distancing, we assumed that close contacts were reduced by 40% and casual contacts by 70%. The resulting effective

	Isolation	Conventional contact tracing	Mobile app contact tracing
Testing coverage	80%	80%	20%, 40%, 60%, 80%, 100%
Testing delay ( $D_1$ ), assuming immediate isolation when testing positive	4 days	4 days	0 days
Time to trace close contacts ( $D_2$ )	..	3 days	0 days
Time to trace other contacts, assuming testing and isolation of those who test positive	..	3 days	0 days
Tracing coverage of close contacts	..	80%	20%, 40%, 60%, 80%, 100%
Tracing coverage of casual contacts	..	50%	20%, 40%, 60%, 80%, 100%
Time traced back	..	7 days	7 days

For isolation-only and conventional contact tracing strategies, we assumed a baseline testing coverage of 80% (see appendix pp 11–12 for sensitivity analyses). For mobile app contact tracing strategies, we varied the testing coverage between 20% and 100%, and assumed 80% as a best-case scenario. For conventional contact tracing, delays and coverages were chosen to reflect current practice, whereas for mobile app contact tracing, we varied coverages to reflect different levels of app use.

**Table 1: Comparison of isolation, conventional contact tracing, and mobile app contact tracing strategies**



**Figure 2: Comparison of conventional and mobile app contact tracing strategies** For parameter values, see table 1. The isolation only strategy is shown in green for comparison. We assumed that testing coverage is 80% for the conventional contact tracing strategy and 60%, 80%, and 100% for the mobile app contact tracing strategy. For the mobile app strategy, it is assumed that the tracing coverage equals the testing coverage—ie, it is 60%, 80%, and 100%, respectively. Expected reproduction numbers are shown as a function of testing delay  $D_1$ .  $R_e$ =effective reproduction number.

reproduction number was  $R_e=1.2$ . More details on the parameters are given in the appendix (pp 2–4).

**Uncertainty of model outcomes**

We considered uncertainty due to stochastic variability and uncertainty due to possible variation in parameter estimates. We dealt with stochastic variability by computing individual reproduction numbers for 1000 individuals for all scenarios and plotted their distributions as boxplots. Parameter uncertainty was explored by performing simulations using hypercube sampling for transmission probabilities and probabilities of symptom onset per day of the infectious period (appendix pp 9–10).

**Scenarios modelled**

For conventional contact tracing, we assumed baseline values of 80% testing coverage and higher tracing coverage for close contacts than for casual contacts, set at 80% and 50%, respectively. We analysed the effect of various testing and tracing delays and tracing coverage on  $R_{CTS}$  while keeping the testing coverage at 80%. For comparison, we also considered the isolation strategy ( $R_{iso}$ ), again with testing coverage at 80%. In sensitivity analyses, we varied the testing delay  $D_1$  between 0 and 7 days and the tracing delay  $D_2$  between 0 and 3 days; furthermore, we varied both testing coverage and tracing coverages separately between 20% and 80% in increments of 20 percentage points.

We then compared the effectiveness of conventional contact tracing alone with a scenario in which mobile app technology is used for alerting people to be tested and for tracing contacts; exact parameter values for this comparison are shown in table 1. Differences between these strategies were taken as follows. The testing delay ( $D_1$ ) is reduced by 4 days with mobile app technology. We assumed a conventional contact tracing setting in which symptomatic individuals need to decide to seek health care to get tested, and we assumed that with app technology, individuals reporting symptoms to the app are automatically offered a test without having to seek health care. For conventional contact tracing, we assumed suboptimal coverage in identifying contacts from the week before diagnosis due to recall bias, especially for casual contacts. For contact tracing with mobile app technology, we assume 80% tracing coverage of the contacts of symptomatic people using mobile app technology as a best-case scenario, but also consider other coverages as detailed below and in table 1. We show also results for 100% coverage, although realistically more than 80% is not feasible because not all contacts will be correctly identified and compliance with isolation of those tested positive might not be perfect. We assume that tracing goes back for 7 days before the positive test result for both strategies.

Next, we quantified the impact of coverage of testing and mobile app use on the effectiveness of different strategies. We varied the percentage of app users in the population between 20% and 100% in increments of 20 percentage points. We first considered the situation where testing is provided for 80% of people with symptoms independently of app use, and app use only influences the fraction of contacts that are traced (ie, tracing coverage varies between 20% and 100%). Alternatively, we assumed that only app users are tested (ie, testing coverage varies between 20% and 100%), and coverage of tracing also depends on fraction of app use. In all cases, a contact could only be traced if both the index case and the contact were app users—ie, the probability of a contact being traced is given by the square of the proportion of app users.

Finally, we quantified the fraction of transmissions of an index case that can be prevented, and the contribution to the fraction prevented from isolation and from tracing contacts with decreasing delays. The number of onward transmissions of an index case is, by definition, described by the effective reproduction number  $R_e$  of the realised scenario. Therefore, the difference of reproduction numbers between two intervention scenarios under the condition that an index case is diagnosed will describe the fraction of onward transmissions prevented. For contacts, this is the fraction of the total infectivity that lies after the time of isolation—ie, the part of infectiousness that is prevented by contact tracing. In other words, a contact person who is detected and isolated before the start of their infectious period is counted as a fully prevented transmission, whereas a contact person who is only traced and identified after 70% of their infectivity has passed is counted as 0.3 of a prevented onward transmission.

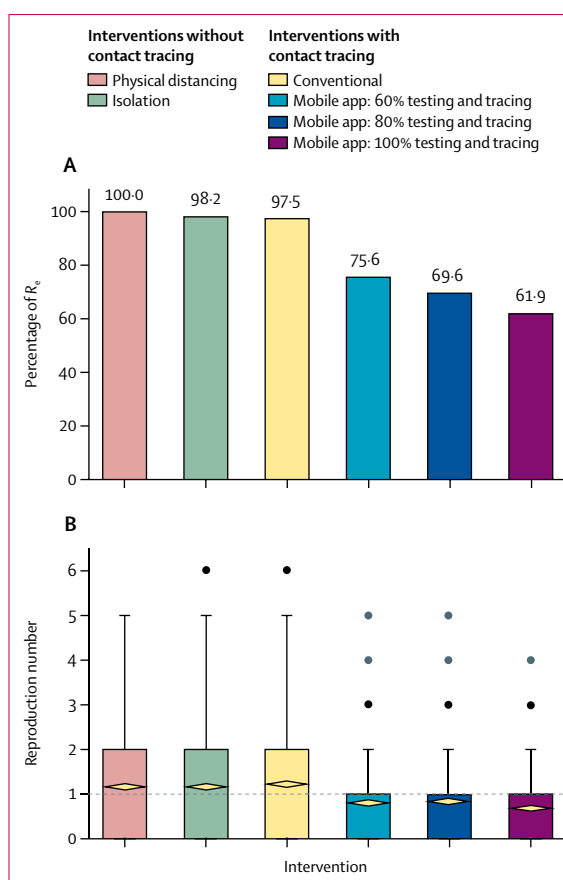
### Role of the funding source

The funders of the study had no role in study design, data collection, data analysis, data interpretation, writing of the manuscript, or the decision to submit for publication. All authors had full access to all the data in the study and were responsible for the decision to submit the manuscript for publication.

## Results

If 80% of infectious people who develop symptoms are tested and isolated within 1 day after symptom onset, the effective reproduction number  $R_e$  is expected to decline from 1.2 to an  $R_{so}$  of 1.0 (95% CI 0.9–1.1), using an isolation strategy without contact tracing (figure 2). Contact tracing has the potential to further decrease the reproduction number to 0.8 (95% CI 0.7–0.9), as shown by the mobile app contact tracing scenario with 100% testing and tracing (figure 2). In our predefined best-case scenario, with 80% testing coverage, testing and tracing delays of 0 days, and a tracing coverage of 80%, the model predicts a 30% reduction of  $R_e$ , down to an  $R_{CTS}$  of 0.8 (0.7–1.0). However, once the testing delay approaches 2 days, tracing delay needs to be at most 1 day or tracing coverage needs to be at least 80% to keep  $R_{CTS}$  below 1 (appendix p 10). From these scenarios, the reduction of  $R_{CTS}$  achieved by implementing the best-case scenario is estimated at 17% (appendix p 10). Once testing delay becomes 3 days or longer, even perfect contact tracing (ie, 100% testing and tracing coverage with no tracing delay) cannot bring  $R_{CTS}$  values below 1.

Our assumption that conventional contact tracing has a longer tracing delay and lower tracing coverage than a strategy based on mobile app technology resulted in marked differences in  $R_{CTS}$  for the whole range of testing delay (figure 2). With conventional contact tracing,  $R_{CTS}$  would remain above 1 if the testing delay exceeds 0 days,



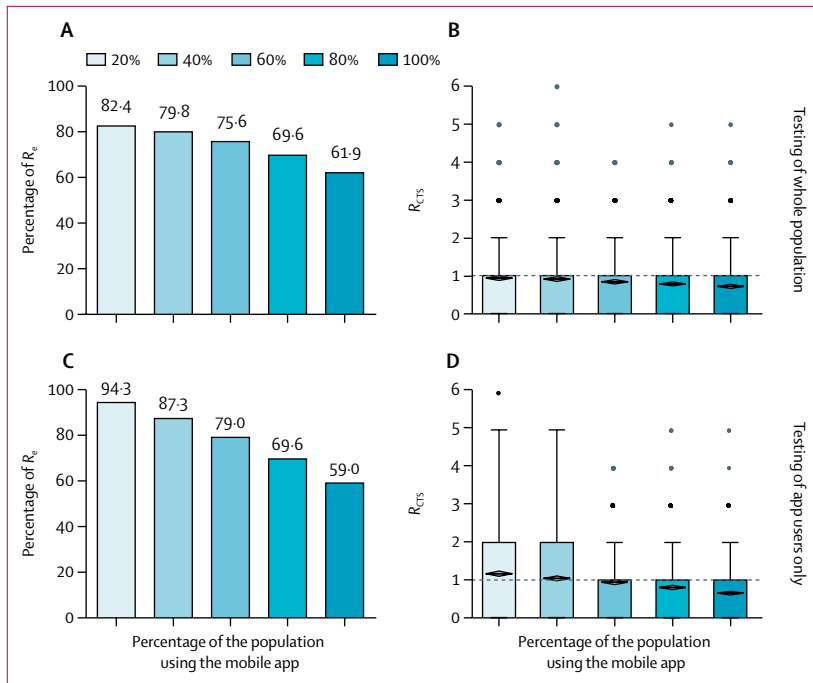
**Figure 3: Estimated reduction of the effective reproduction number for various contact tracing strategies**

(A)  $R_{CTS}$  is shown as a percentage of  $R_e$ , where only physical distancing is implemented. For the isolation scenario and conventional contact tracing scenario, we assumed a 4-day delay between symptom onset and isolation of the index case. For mobile app contact tracing, testing delay was assumed to be 0 days. Testing coverage was assumed to be 80% in the isolation and conventional contact tracing scenarios; app use prevalence was assumed to be 60%, 80%, and 100% in the mobile app contact tracing scenarios.

(B) Distributions of individual reproduction numbers for 1000 individuals in the same scenarios as in described in panel A. Each boxplot shows the mean (diamond, where the height of the diamond indicates the CI of the mean) IQR, and upper fence (75% quartile + 1.5 × IQR) of the distribution. The dots are outliers, where darker dots contain more datapoints than lighter dots. All datapoints are integers.  $R_e$ =effective reproduction number.  $R_{CTS}$ =effective reproduction number with contact tracing.

whereas contact tracing based on mobile app technology could still keep  $R_{CTS}$  below 1 with a delay of up to 2 days, as long as testing and tracing coverage are at least 80%, or with a testing delay of 1 day if tracing coverage is at least 60%. If the testing delay reaches 5 days or more, app technology adds little effectiveness to conventional contact tracing or just isolation of symptomatic cases.

The reductions of  $R_e$  (based on physical distancing) achieved by isolation of symptomatic cases only, conventional contact tracing, and mobile app-based contact tracing are shown in figure 3A. For isolation only and for conventional contact tracing, we assumed a delay of 4 days between symptom onset and isolation of the index case.



**Figure 4: Impact of varying levels of mobile app use on  $R_{ets}$**   
 In panels A and B, we assume that there is also testing (at 80% coverage) of those who do not use the mobile app, so app use only is used for tracing contacts. In panels C and D, only app users, who develop symptoms, are tested. Panels A and C show percentage reductions of  $R_e$  achieved by the mobile app contact tracing strategy; panels B and D show the impact of various contact tracing strategies on distributions of individual reproduction numbers,  $R_{ets}$ . Each boxplot shows the mean (diamond), where the height of the diamond indicates the CI of the mean) IQR, and upper fence (75% quartile + 1.5 × IQR) of the distribution. The dots are outliers, where darker dots contain more datapoints than lighter dots. All datapoints are integers.  $R_e$ =effective reproduction number.  $R_{ets}$ =effective reproduction number with contact tracing.

	Isolation only	Isolation plus contact tracing			
		$D_t=3$	$D_t=2$	$D_t=1$	$D_t=0$
$D_i=0$	50.4%	62.4%	67.8%	73.9%	79.9%
$D_i=1$	35.7%	47.3%	53.4%	60.7%	68.5%
$D_i=2$	23.4%	33.0%	38.9%	46.5%	55.4%
$D_i=3$	14.2%	21.0%	26.0%	32.9%	41.8%
$D_i=4$	7.8%	11.9%	15.7%	21.4%	29.1%
$D_i=5$	3.8%	5.9%	8.4%	12.5%	18.4%
$D_i=6$	1.6%	2.4%	3.8%	6.4%	10.4%
$D_i=7$	0.5%	0.7%	1.3%	2.8%	4.9%

Interventions explored are isolation of only the index case or isolation of the index case with tracing and isolation of 80% of infected contacts, according to tracing delay  $D_t$ , ranging from 0 to 3 days. All interventions are varied by testing delay  $D_i$ , ranging from 0 to 7 days.

**Table 2: Percentage of onward transmissions prevented per diagnosed index case for various interventions**

The relative reductions are independent of the level of  $R_e$ , with similar percentage reductions seen when starting from  $R_e$ —ie, in a situation without physical distancing (appendix p 14). At 80% testing coverage, conventional contact tracing, even if applied for all infected individuals with symptoms, is less effective than mobile app-based

contact tracing (difference 27.9 percentage points), due to longer tracing delays and lower tracing coverage (figure 3; table 1). When considering the distributions of individual reproduction numbers for the assumed testing delays—ie, 4 days for isolation and conventional contact tracing and 0 days for app-based contact tracing—we found that the mean reproduction number was less than 1 only for mobile app-based contact tracing (figure 3).

The effectiveness of mobile app-based technology declines with lower fractions of the population using it (figure 4). Yet, app-based tracing on its own remains more effective than conventional tracing alone, even with 20% coverage, due to its inherent speed. Even with low coverage, there is a reduction of  $R_e$ , due to fast tracing of a small part of the population. Depending on  $R_e$ , such an approach might be sufficient to reduce  $R_{ets}$  to levels below 1. This can be seen in the distributions of  $R_{ets}$ : when the app is used only for contact tracing (ie, all symptomatic individuals can be tested, regardless of whether they use the app), the means of the  $R_{ets}$  distributions are below 1 when at least 40% of the population are using the app, whereas when the app is used for contact tracing and testing (ie, only app users can be tested), this is the case when at least 60% of the population are using the app (figure 4).

We quantified proportions of transmissions per index case that can be prevented depending on testing delay, stratified by isolation of index cases and tracing delays (table 2). In the best-case scenario, with testing and tracing delays of 0 days, 79.9% of transmissions can be prevented if the tracing coverage is 80%. When testing delay is increased to 3 days with a tracing delay of 0 days, the percentage of transmission prevented is almost halved to 41.8%. If tracing delay is also increased to 3 days, only 21.0% of onward transmissions can still be prevented.

### Discussion

Using a mathematical model that describes the different steps of a contact tracing strategy for COVID-19, we have quantified the relevance of delays and coverage proportions for controlling SARS-CoV-2 transmission. We conclude that reducing the testing delay—ie, shortening the time between symptom onset and a positive test result, assuming immediate isolation—is the most important factor for improving contact tracing effectiveness. Reducing the tracing delay—ie, shortening the time to trace contacts, assuming immediate testing and isolation if found positive—might further enhance contact tracing effectiveness. Yet this additional effect rapidly declines with increasing testing delay. The effectiveness of mobile app-based contact tracing declines with lower app use coverage, but it remains more effective than conventional contact tracing even with lower coverage, due to its inherent speed. If an index case is tested positive and enters this information into the app, other users who have been in contact can be warned immediately, because the app will have recorded these contacts via Bluetooth.

A contact tracing strategy therefore has the potential to control virus transmission, and to enable alleviation of other control measures, but only if all delays are maximally reduced. It should be noted that we simulated two contact tracing systems—conventional contact tracing with testing and tracing delays and app-based contact tracing without delays—and ignored hybrid approaches. At present, most European countries are using conventional contact tracing strategies, but are attempting to reduce delays (eg, by improving testing and tracing capacity and by removing testing barriers), and are piloting or planning the addition of app-based contact tracing. Such hybrid contact tracing systems would fall somewhere between the fully conventional and app-based scenarios described in this Article.

Several factors can reduce the effectiveness of contact tracing, such as large proportions of cases who remain asymptomatic or are otherwise not diagnosed and large proportions of contacts who cannot be traced. Mobile app-based technology could increase the proportion of traceable contacts because it does not rely on recall of names and contact details, but this would require the participation of a substantial proportion of the population. App use acceptance might be hampered by privacy concerns and other ethical considerations. Also, app use needs to continue over a long time period, requiring sustained adherence by app users. Low participation does not render contact tracing useless, however, because it could help to locally extinguish clusters before they grow larger. In addition, every measure that lowers the effective reproduction number, even if it is already below 1, will lower the cumulative case number and speed up the time until elimination of the virus from the population.

A strength of our approach is that it explicitly takes many details of the contact tracing process into account, such that the key factors can be identified. A limitation of our approach is that it does not take population age structure into account, which might influence the proportion of asymptomatic cases and mobile app use coverage. Also, the willingness of a case to self-isolate depends on age and social norms, might be influenced by socioeconomic status, and is affected by perceived benefit of isolation in relation to perceived risk of the infection to others.<sup>25</sup> We also excluded other heterogeneities while assuming homogeneous mixing,<sup>26,27</sup> and assumed homogeneously distributed use of app technology for different coverage levels. Clustering of non-users could have consequences for the overall effectiveness of contact tracing, similar to clustering of non-vaccinated people. Furthermore, we ignored that a sizeable portion of transmissions might be acquired nosocomially when population prevalence is still low.<sup>28</sup> The model also ignores that some contacts of the index case might have self-quarantined with symptoms before they are traced, which lowers the benefits of a contact tracing strategy.

Our study adds to results from other modelling studies, which have shown that contact tracing can be an effective

intervention if tracing coverage is high and if the process is fast.<sup>2,15</sup> A determining factor is the proportion of transmissions occurring before symptom onset, which determines the urgency of tracing and isolating contacts as fast as possible. Our study showed in detail what the role is of each step in the contact tracing process in making it successful. Our model differs from other published models in that it makes a distinction between close and casual contacts and we consider scenarios for conventional contact tracing and mobile app-based contact tracing characterised by specific delays and coverages.

Our finding of the crucial importance of the first step of contact tracing—establishing a diagnosis in cases with symptoms—has important consequences. It requires an infrastructure for testing that allows people with symptoms to be quickly tested and alerted to their results, preferably within 1 day of symptom onset. For example, walk-in or drive-in testing facilities could be set up on a large scale and test results immediately communicated via the tracing app. Studies have shown that the sensitivity of current PCR tests is low during the first 3 days after infection due to low but steadily increasing viral load in the respiratory tract;<sup>29,30</sup> testing on the fourth day after infection, regardless of symptoms, might therefore be optimal. However, when more sensitive PCR tests become available, earlier testing might further enhance effectiveness. As the clinical symptoms of COVID-19 are mostly mild and heterogeneous, many people should be eligible for testing, resulting in a large proportion of negative test results. Future work should determine the optimal balance between the proportion of negative tests and the effectiveness of contact tracing.

Our findings also provide strong support to optimise contact tracing. In the Netherlands, the contact tracing strategy was based on establishing contact between an index case and a public health officer, followed by an interview after which contacts are traced. This procedure is labour intensive, time consuming, prone to recall bias, incomplete (anonymous contacts cannot be traced), and usually takes several days. Optimising this process by improving testing and tracing capacity, removing testing barriers, and by adding app-based or other digital technologies to minimise tracing delay is needed to establish optimal control of transmission. These improvements are currently being implemented or considered. Overall, our findings suggest that an optimised contact tracing strategy, with short delays and high coverage for testing and tracing, could substantially reduce the reproduction number, which would allow alleviation of more stringent control measures.

#### Contributors

MEK and MJMB conceived the study. MEK designed and programmed the model and produced the output. MvB, MCJB, and GR helped with the analysis and literature research. JHHMvdW contributed to data interpretation and writing. All authors interpreted the results, contributed to writing the manuscript, and approved the final version for submission.

**Declaration of interests**

We declare no competing interests.

**Data sharing**

The Mathematica code used for the analysis are available on GitHub.

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For the Mathematica code see  
<https://github.com/mirjamkretzschmar/ContacttracingModel>