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4 **Time is of the essence: impact of delays on effectiveness of contact tracing**

5 **for COVID-19, a modelling study**

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Summary

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32   **Background**

33   With confirmed cases of COVID-19 declining in many countries, lockdown measures are

34   gradually being lifted. However, even if most social distancing measures are continued,

35   other public health measures will be needed to control the epidemic. Contact tracing via

36   conventional methods or mobile app technology is central to control strategies during de-

37   escalation of social distancing. We aimed to identify key factors for a contact tracing

38   strategy (CTS) to be successful.

39

40   **Methods**

41   We evaluated the impact of timeliness and completeness in various steps of a CTS using a

42   stochastic mathematical model with explicit time delays between time of infection and

43   symptom onset, and between symptom onset, diagnosis by testing, and isolation (testing

44   delay). The model also includes tracing of close contacts (e.g. household members) and

45   casual contacts, followed by testing regardless of symptoms and isolation if positive, with

46   different delays (tracing delay) and coverages (tracing coverage). We computed effective

47   reproduction numbers of a CTS (R_{cts}) for a population with social distancing measures and

48   various scenarios for isolation of index cases and tracing and quarantine of its contacts.

49

50   **Findings**

51   For the best-case scenario (testing and tracing delays of 0 days and tracing coverage of

52   80%), and assuming that around 40% of transmission occur before symptom onset, the

53   model predicts that the effective reproduction number of 1.2 (with social distancing only)

54   will be reduced to 0.8 by adding contact tracing. A testing delay of 2 days requires tracing

55   delay to be at most 1 day, or tracing coverage to be at least 80% to keep R_{cts} below 1. With a

56   testing/isolation delay of 3 days, even the most efficient CTS cannot reach R_{cts} values below

57   1. The effect of minimizing tracing delay (e.g., with app-based technology) declines with

58   decreasing coverage of app use, but app-based tracing alone remains more effective than

59   conventional tracing alone even with 20% coverage. The proportion of transmissions per

60   index case that can be prevented depends on testing and tracing delays, and ranges from up

61   to 80% in the best-case scenario (testing and tracing delays of 0 days) to 42% with a 3-day

62   testing delay and 18% with a 5-day testing delay.

63

64   **Interpretation**

65   In our model, minimizing testing delay had the largest impact on reducing onward

66   transmissions. Optimizing testing and tracing coverage and minimizing tracing delays, for

67   instance with app-based technology, further enhanced CTS effectiveness, with a potential to

68   prevent up to 80% of all transmissions. Access to testing should therefore be optimized, and

69   mobile app technology may reduce delays in the CTS process and optimize contact tracing

70   coverage.

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Research in context

Evidence before this study

We searched PubMed, bioRxiv, and medRxiv for articles published in English from January 1, 2020, 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 (CTS) in order 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 performed 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 which makes a distinction between close contacts (e.g. household members) and casual contacts to assess which steps and (possible) delays are crucial in determining the effectiveness of CTS. We evaluated how delays and the level of contact tracing coverage influence the effective reproduction number, and how fast CTS needs to be to keep the reproduction number below 1. We also analyzed what proportion of onward transmission can be prevented for

98   short delays and high contact tracing coverage. Assuming that around 40% of transmission

99   occurs before symptom onset, we found that keeping the time between symptom onset and

100   testing and isolation of an index case short (<3 days) is imperative for a successful CTS. This

101   implies that the process leading from symptom onset to receiving a positive test should be

102   minimized by providing sufficient and easily accessible testing facilities. In addition, reducing

103   contact-tracing delays also helps to keep the reproduction number below 1.

104

105   **Implications of all the available evidence**

106   Our analyses highlight that CTS will only contribute to containment of COVID-19 if it can be

107   organised in a way that time delays in the process from symptom onset to isolation of the

108   index case and his/her contacts are very short. The process of conventional contact tracing

109   should be reviewed and streamlined, while mobile app technology may offer a tool for

110   gaining speed in the process. Reducing delay in testing subjects for SARS-CoV-2 should be a

111   key objective of CTS.

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Introduction

As the first wave of the SARS-CoV-2 has reached its peak of cases in many countries,

societies are preparing so-called exit-strategies from the COVID-19 lockdown, while still

successfully controlling transmission. Contact tracing, in combination with quarantine and

potentially testing of the contacts, is considered a key component in a phase when lockdown

measures are gradually lifted[1-8]. Contact tracing is an intervention, where an index case with

confirmed infection is asked to provide information about contact persons, who were at risk

of acquiring infection from the index case within a given time period before the positive test

result. These contact persons 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 apps to support contact

tracing is widely discussed and such technology has been used in several Asian countries.

Although these countries have successfully reduced case numbers, no causal relationship

between use of app technology and epidemic control has yet been shown[9-14]. Many

uncertainties remain on the optimal process of contact tracing with conventional methods

and/or mobile applications, on the timing of testing for current or past infection, and on the

required coverage of contact tracing needed.

Modelling studies have demonstrated how mobile applications can increase effectiveness of

contact tracing, compared to conventional approaches for contact tracing, but effectiveness

depends on what proportion of the population will use the app consistently for a sufficiently

long period of time[9]. Modelling studies have predicted that contact tracing alone cannot

control an outbreak if tracing coverage is too low[2,15]. What tracing coverage is needed

depends on how much transmission occurs before symptom onset, and on the details of the

tracing process.

139

140   In previous work, we have investigated the impact of timeliness and completeness of case

141   reporting for the effectiveness of surveillance and interventions[16,17], and we quantified the

142   timeliness of contact tracing of infected passengers during an airline flight for the 2009

143   pandemic influenza[18]. In all of these studies, the timing of various steps in the monitoring and

144   intervention chain emerged as one of the key factors for effectiveness of a public health

145   response. Usually, there are identifiable delays in the response chain that may be critical to

146   the overall effectiveness of a strategy.

147

148   Here we analyze in detail the process chain of identifying index cases by symptom-reporting

149   followed by testing, and subsequent contact tracing, with the aim to inform policy makers on

150   the relative importance of key steps in the process. We use a mathematical model that reflects

151   the various steps and delays in the contact tracing process to quantify the impact of delays on

152   the effective reproduction number and the fraction of onward transmission prevented per

153   diagnosed index case[5,19].

154

155 # Methods

156   **Time delays in contact tracing**

157   Our starting point is an assumed effective reproduction number (R_e) for COVID-19 of around

158   1, describing a situation with "social distancing but measures lifted to some extent". We then

159   quantify the relative contribution of the individual components of a contact tracing strategy

160   (CTS) required to bring and maintain the effective reproduction number with CTS (R_{CTS}) to a

161   value below 1. For simplicity we do not include transmission in healthcare settings, as in

162   healthcare settings like nursing homes, which can be viewed as closed populations, other

163   interventions are more appropriate.

164   We break down the process of contact tracing in two steps (Figure 1; Supplementary

165   Information Table S1).

166   •   An index case acquires infection (at time T_0), then after a short latent period becomes

167   infectious (at time T_1), and finally symptomatic (at time T_2), which is here defined as

168   "being eligible for testing". Subsequently a proportion of all symptomatic subjects gets

169   tested and diagnosed (at time T_3). The time between T_2 and T_3 is called the "testing

170   delay" ($D_1 = T_3 - T_2$), and may vary between 0 and 7 days, and in this period individuals

171   might self-quarantine. We refer to the proportion of all symptomatically infected cases

172   that are tested as testing coverage and vary it from 20% to 80% in increments of 20%.

173   After being diagnosed, we assume index cases are isolated with no further transmission.

174   •   The second step is tracing contacts of the index case, which occurs at time T_4. A fraction

175   of those contacts will be found and tested. We assumed that all contacts, regardless of

176   symptoms, are offered testing, and that those testing negative do not spread. Those who

177   are found infected will be isolated, with effectiveness ranging from 0% to 100%. We

178   assume that contacts in isolation do not spread. The time between T_3 and T_4 is the

179   "tracing delay" ($D_2 = T_4 - T_3$), which may range from 0 (for instance with app

180   technology) to 3 days (with conventional approaches). In this step, tracing coverage is

181   defined as the proportion of contacts detected, which either depends on the capacity of

182   conventional approaches (ranging from 20% to 80% in increments of 20%) or on the

183   fraction of the population using suitable app technology for screening (ranging from 20%

184   to 100% in increments of 20%). We did not consider hybrid approaches of combined

185   conventional and app-based CTS.

186   The best-case scenario we consider is that persons eligible for testing are immediately tested

187   (coverage 80%) with a very fast test result (test-delay 0 days) and immediate isolation when

188   testing positive, followed by immediate tracing (trace delay 0 days) of all contacts, that

189   immediately adhere to isolation measures (coverage 80%). We consider more realistic

190   scenarios where testing and tracing are suboptimal, e.g. a conventional CTS, and we vary

191   these parameters separately in a sensitivity analysis (see Supplementary Information).

192

Impact on effectiveness on population level

194   To analyse the impact of these time delays on the effectiveness of contact tracing we use a

195   model introduced by Kretzschmar et al[19], which was adapted for SARS-CoV-2[5]. The

196   stochastic model describes an epidemic as a branching process with progression through

197   latent infection and infectious period in time steps of 1 day. Infectivity and probability of

198   symptom onset per day of the infectious period, and numbers of contacts per day were fitted

199   to distributions taken from published data. [20-24] We distinguish between close contacts (e.g.

200   household contacts, but also other high-risk contacts) and casual contacts, which differ in the

201   risk of acquiring infection from the index case. Also, the time required for tracing and

202   isolating infected contacts and the coverage of tracing may differ between these types of

203   contacts and between different CTS (i.e., conventional contact tracing versus mobile app

204   supported contact tracing). We assume that isolation is perfect, i.e. that isolated persons do

205   not transmit any longer, and that all traced infected contacts are isolated, regardless of

206   whether they develop symptoms or not. The model allows for explicit computation of the

207   basic reproduction number R_0, the effective reproduction number under social-distancing

208   interventions R_e, and the effective reproduction number with CTS (R_{cts}). Reproduction

209   numbers were calculated as expectations, and distributions of individual reproduction

210   numbers were simulated. The model was coded in Mathematica 12.1. For details, see the

211   Supplementary Information.

212

Parameter settings

214   We assumed that without social distancing individuals have on average 4 close contacts per

215   day and around 9 casual contacts per day, with stochastic variability. The distributions were

216   fitted to data from the Polymod study for the Netherlands[23]. Transmission probability per

217   contact for close contacts was taken to be 4 times higher than for casual contacts.

218   Symptomatic and asymptomatic cases were assumed to be equally infectious. Overall, the

219   transmission probability was calibrated to a basic reproduction number of $R_0 = 2.5$. For

220   social distancing, we assumed that close contacts were reduced by 40% and casual contacts

221   by 70%. The resulting effective reproduction number was $R_e = 1.2$.

222

Uncertainty of model outcomes

224   We considered uncertainty due to stochastic variability, and uncertainty due to possible

225   variation in parameter estimates. We dealt with stochastic variability by computing

226   individual reproduction numbers for 1000 individuals for all scenarios, and plotted their

227   distributions as boxplots. Parameter uncertainty was explored by performing simulations

228   using hypercube sampling for transmission probabilities and probabilities of symptom onset

229   per day of the infectious period (Supplementary Information).

230

Scenarios modelled

232   We analyzed the impact of various testing and tracing delays and tracing coverage on the

233   effective reproduction number R_{cts} while keeping the testing coverage at 80%. For

234   comparison, we also considered the strategy where symptomatic individuals get tested and

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235   isolated, without subsequent tracing (R_{iso}). We varied the testing delay D_1 between 0 and 7

236   days, the tracing delay D_2 between 0 and 3 days, and tracing coverages between 0% and

237   100% in increments of 20%. For conventional contact tracing, we assumed that coverage is

238   higher for close contacts than for casual contacts.

239

240   We then compared the effectiveness of conventional CTS alone with a scenario in which

241   mobile app technology is used for alerting subjects to be tested and for tracing contacts.

242   Differences between these strategies were taken as follows. The testing delay (D_1) is reduced

243   with app technology. We assumed a conventional CTS setting in which symptomatic

244   individuals need to decide to seek health care to get tested, and we assumed that with app

245   technology symptomatic persons get alerted and can be tested without health care

246   interference. For conventional CTS we assumed suboptimal coverage in identifying contacts

247   from the week before diagnosis due to recall bias, especially for casual contacts. For CTS

248   with mobile app technology we assume 60% and 80% tracing coverage of the contacts of

249   subjects using app technology. We show also results for 100% coverage, although

250   realistically more than 80% is not feasible, because not all contacts may be correctly

251   identified and compliance with isolation of those tested positive may not be perfect. We

252   assume that tracing goes back for 7 days before the positive test result. The exact parameter

253   values for this comparison are shown in Table 1.

254

255   Next, we quantified the impact of coverage of testing and app use on the effectiveness of

256   CTS. We varied the percentage of app users in the population between 20% and 100% in

257   increments of 20%. We first considered the situation that testing is provided for 80% of

258   persons with symptoms independent of app use, and app use only influences the fraction of

259   contacts that are traced. Alternatively, assumed that only app users are tested (i.e. testing

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260   coverage varies between 20% and 100% in increments of 20%), and coverage of tracing also

261   depends on fraction of app use. In all cases, a contact person could only be traced if both the

262   index case and the contact person were app users, i.e. the probability of a contact being traced

263   is given by the square of the proportion of app users.

264

265   Finally, we quantified the fraction of transmissions of an index person that can be prevented,

266   and the contribution to the fraction prevented from isolation and from tracing contacts with

267   decreasing delays. The number of onward transmissions of an index case is by definition

268   described by the effective reproduction number of the realized scenario. Therefore, the

269   difference of reproduction numbers between two intervention scenarios under the condition

270   that an index case is diagnosed, describes the fraction of onward transmissions prevented. For

271   contact persons, this is the fraction of the total infectivity that lies after the time of isolation,

272   i.e. the part of infectiousness that is prevented by contact tracing. In other words, a contact

273   person who is detected and isolated before the start of their infectious period is a fully

274   prevented transmission, while a contact person who is only traced and identified after 70% of

275   their infectivity has passed, is counted as 0.3 of a prevented onward transmission.

276

277   **Role of the funding source**

282

283   # Results

284   In the best-case scenario, if 80% of infectious persons that develop symptoms are tested and

285   isolated within 1 day after symptom onset the effective reproduction number R_e is expected

286   to decline from 1.2 to $R_{iso} = 1.0$, without contact tracing (Figure 2). Contact tracing may

287   further decrease the reproduction number to R_{cts}=0.8 in the best case scenario. In the best

288   case scenario – a testing delay of 0 days, a tracing delay of 0 days, and a tracing coverage of

289   80%, the additional reduction of R_{cts} predicted by the model is 33%. Yet, with a testing delay

290   of 2 days, tracing delay should be at most 1 day, or tracing coverage should be at least 80% to

291   keep R_{cts} below 1. In these scenarios, the reduction of R_{cts} compared to the best-case scenario

292   is estimated at 17% (Supplementary Information Figure S4). With a testing delay of more

293   than 3 days, even perfect contact tracing cannot bring R_{cts} values below 1.

294

295   We assumed that conventional CTS has longer tracing delay and lower tracing coverage than

296   CTS based on app technology which results in marked differences in R_{cts} for the whole range

297   of testing delay (Figure 2A). With conventional CTS, R_{cts} would remain above 1, if the

298   testing delay exceeds 0 days, whereas contact tracing based on app technology could still

299   keep R_{cts} below 1, as long as testing and tracing coverage would be at least 80%, or if testing

300   delay is 1 day and tracing coverage 60%. If the testing delay reaches 5 days or more, app

301   technology adds little effectiveness to conventional CTS or just isolating symptomatic cases.

302

303   The reductions of R_e (based on social distancing) achieved by isolation of symptomatic cases

304   only, conventional CTS, and mobile app-based CTS are shown in figure 3A. For isolation

305   only and for conventional CTS we assumed a delay of 4 days between symptom onset and

306   isolation of the index case. The relative reductions are independent of the level of R_e, similar

307   reductions are seen for R_0, i.e. in a situation without social distancing (Supplementary

308   Information). Conventional CTS, even if applied for all infected subjects with symptoms, is

309   27% less effective than mobile app-based CTS alone, due to longer tracing delays and lower

310   tracing coverage. Figure 3B shows the distributions of individual reproduction numbers for

311   the testing delays assumed in Table 1, i.e. 4 days for isolation and conventional CT, and 0

312   days for app-based CTS. Only for app-based CTS the means of the individual reproduction

313   numbers are below 1.

314

315   The effectiveness of app-based technology declines with lower fractions of persons using it

316   (Figure 4). Yet, app-based tracing on its own remains more effective than conventional

317   tracing alone, even with 20% coverage, due to its inherent speed. Even with low coverage

318   there is a reduction of R_e, due to fast tracing of a small part of the population. Depending on

319   R_e, such an approach might be sufficient to reduce R_{cts} to levels below 1. This can be seen in

320   the distributions of the individual reproduction numbers (Figure 4B and 4D), where in 4B the

321   means of the distributions are below 1 for 40% and more app use, while in 4D this is the case

322   for 60% and above.

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325   In Table 2, we quantified proportions of transmissions per index case that can be prevented

326   depending on testing delay, stratified by of isolation of index cases and tracing delays. In the

327   best-case scenario (testing and tracing delay being 0 days) around 80% of transmissions can

328   be prevented if tracing coverage is 80%.

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Discussion

333   Using a mathematical model that describes the different steps of CTS for COVID-19 we have

334   quantified the relevance of delays and coverage proportions for controlling SARS-CoV-2

335   transmission. We conclude that reducing the testing delay, i.e. shortening the time between

336   symptom onset and positive test result (assuming immediate isolation), is the most important

337 factor for improving CTS effectiveness. Reducing the tracing delay, i.e. shortening the time

338 of contact tracing (assuming immediate testing and isolation if positive), may further enhance

339 CTS effectiveness. Yet this additional effect rapidly declines with increasing testing delay.

340 The effectiveness of app-based CTS declines with lower app use coverage, but it remains

341 more effective than conventional contact tracing even with lower coverage, due to its

342 inherent speed. CTS therefore has the potential to control virus transmission, and to enable

343 alleviation of other control measures, but only if all delays are maximally reduced. It should

344 be noted that we simulated two CTS systems (conventional CTS with testing and tracing

345 delays and app-based CTS without delays) and ignored hybrid approaches. At present, most

346 European countries are using conventional CTS, but are attempting to reduce delays (for

347 example, by improving testing and tracing capacity and by removing testing barriers), and are

348 piloting or planning the addition of app-based contact-tracing. Such hybrid CTS systems

349 would fall somewhere between the fully conventional and app-based scenarios described in

350 this paper.

351

352 Several factors can reduce CTS effectiveness, such as large proportions of cases who remain

353 asymptomatic or are otherwise not diagnosed, and large proportions of contacts who cannot

354 be traced. App-based technology could increase the proportion of tracable contacts, because

355 it does not rely on recall of names and contact details, but this would require the participation

356 of a substantial proportion of the population. App use acceptance may be hampered by

357 privacy concerns and other ethical considerations, which limit its acceptance.   Also, app use

358 needs to continue over a long time period, requiring sustained adherence by app users. Low

359 participation does not render CTS useless, however, because it could help to locally

360 extinguish clusters before they grow larger. In addition, every measure that lowers the

361   effective reproduction number, even if it is already below 1, will lower the cumulative case

362   number and speed up the time until elimination of the virus from the population.

363

364   The strength of our approach is that it explicitly takes many details of the contact tracing

365   process into account, such that the key factors can be identified. A limitation of our approach

366   is that it does not take population age-structure into account, which may influence the

367   proportion of asymptomatic cases and mobile app use coverage. Also, the willingness of a

368   case to self-isolate depends on age and social norms, may depend on socio-economic status,

369   and is affected by perceived benefit of isolation in relation to perceived risk of the infection

370   to others[25]. We also excluded other heterogeneities while assuming homogeneous mixing[26,27],

371   and assumed homogeneously distributed use of app technology for different coverage levels.

372   Clustering of non-users may have consequences for overall effectiveness of CTS, similar to

373   clustering of non-vaccinated persons. Furthermore, we ignored that a sizeable portion of

374   transmissions may be acquired nosocomially when population prevalence is still low. [28] The

375   model also ignores that some contacts of the index case may have self-quarantined with

376   symptoms before they are traced by CTS, which lowers the benefits of CTS.

377

378   Our results add to results from other modelling studies, which showed that CTS can be an

379   effective intervention if tracing coverage is high and if the process is fast[2,15]. A determining

380   factor is the proportion of transmissions occurring before symptom onset, which determines

381   the urgency of tracing and isolating contacts as fast as possible. Our study showed in detail

382   what the role is of each step in the CTS process in making it successful. Our model differs in

383   that it makes a distinction between close and casual contacts, and that we consider scenarios

384   for conventional CTS and mobile app-based CTS characterized by specific delays and

385   coverages.

386

387 Our finding of the crucial importance of the first step of CTS, establishing a diagnosis in

388 cases with symptoms, has important consequences. It requires an infrastructure for testing,

389 that allows persons with symptoms to be tested, preferably, within one day of symptom onset.

390 Studies have demonstrated that viral shedding in the respiratory tract is highest at the start of

391 symptoms[29,30], so early testing will also increase the sensitivity of this approach. To further

392 enhance effectiveness, as many infectious persons as possible need to be tested regardless of

393 symptoms, which requires a low threshold for testing. As the clinical symptoms of COVID-

394 19 are mostly mild and heterogeneous, many persons should be eligible for testing, resulting

395 in a large proportion of negative test results. Future work should determine the optimal

396 balance between the proportion of test-negatives and the effectiveness of CTS.

397

398 Our findings also provide strong support to optimize contact tracing. In the Netherlands, CTS

399 was based on establishing contact between an index case and a public health officer, followed

400 by an interview after which contacts are traced. This procedure is labor intensive, time

401 consuming, prone to recall bias, incomplete (anonymous contacts cannot be traced), and

402 usually takes several days. Optimizing this process by improving testing and tracing capacity,

403 removing testing barriers, and by adding app-based and/or other digital technologies to

404 minimize tracing delay are needed to establish optimal control of transmission. These

405 improvements are currently being implemented or considered. Overall, our findings suggest

406 that optimized CTS, with short delays and high coverage for testing and tracing could

407 substantially reduce the reproduction number, which would allow alleviation of more

408 stringent control measures.

409

410 **Data availability**

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411   The Mathematica code used for the analysis are available on Github under

412   https://github.com/mirjamkretzschmar/ContacttracingModel

413

Contributors

415   MEK and MB conceived the study. MK designed and programmed the model, and produced

416   output. MvB, MCJB, and GR helped with the analysis and literature research. JvdW

417   contributed to data interpretation and writing. All authors interpreted the results, contributed

418   to writing the manuscript, and approved the final version for submission.

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Declaration of interests

421   We declare no competing interests.

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511   **Table 1: Comparison Conventional CT and Mobile app CT**

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

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515 **Table 2.** Percentage of onward transmissions prevented per diagnosed index case for various
516 interventions: only isolation of the index case (left column) or isolation of the index case with tracing
517 and isolation of 80% of infected contacts (columns 2-5).
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	Isolation only	Contact tracing Delay D_2 (days)			
Delay D_1 (days)		**3**	**2**	**1**	**0**
0	50.4	62.4	67.8	73.9	79.9
1	35.7	47.3	53.4	60.7	68.5
2	23.4	33.0	38.9	46.5	55.4
3	14.2	21.0	26.0	32.9	41.8
4	7.8	11.9	15.7	21.4	29.1
5	3.8	5.9	8.4	12.5	18.4
6	1.6	2.4	3.8	6.4	10.4

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521 **Figure 1: Schematic of the contact tracing process and its time delays.**
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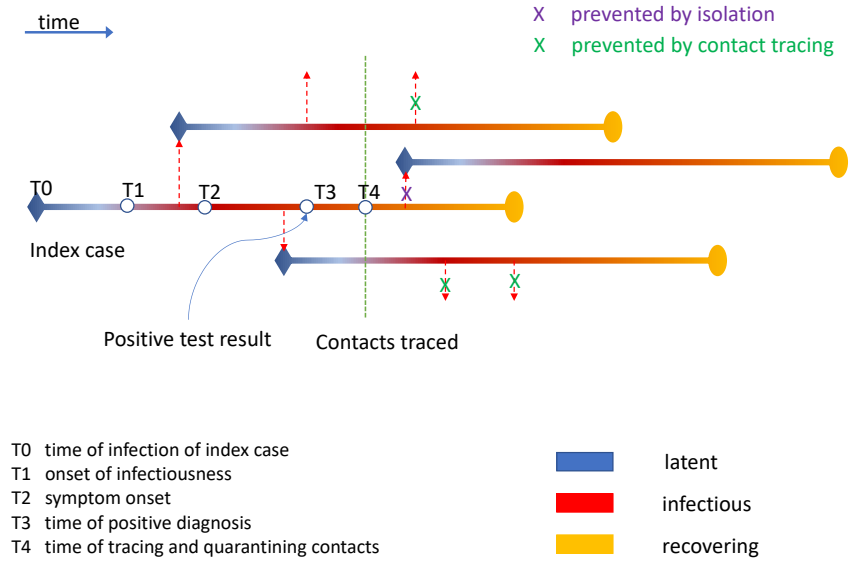
Figure 2: Comparison of a conventional and mobile app CTS. For parameter values, see table 1. We assumed that testing coverage is 80% for the conventional CTS and 60%, 80%, and 100% for the mobile app CTS. For mobile app CTS it is assumed that the tracing coverage equals the testing rate, i.e. it is 60%, 80%, and 100%, respectively. Expected reproduction numbers are shown as a function of testing delay D_1.
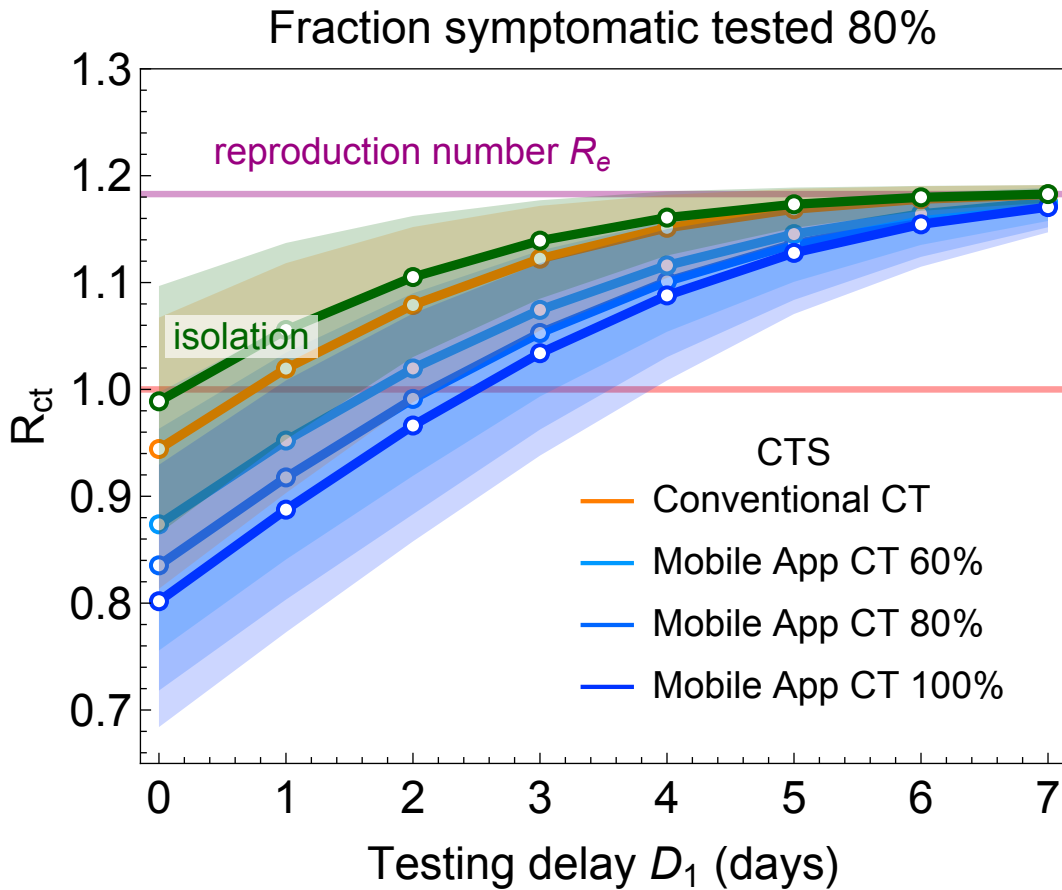
544 **Figure 3: The reduction of the effective reproduction number for various CTS.** (A) The
545 reproduction number with CTS, R_{cts}, is shown as a percentage of the reproduction number where only
546 social distancing is implemented (R_e). For the isolation scenario and conventional tracing scenario we
547 assumed that there is a delay of 4 days between symptom onset and isolation of the index case. For
548 the mobile app CTS, testing delay was assumed to be 0 days. Testing coverage was assumed to be
549 80% in the isolation and conventional CT scenarios; app use prevalence was assumed to be 60%,
550 80%, and 100% in the mobile app CTS. (B) Distributions of individual reproduction numbers for
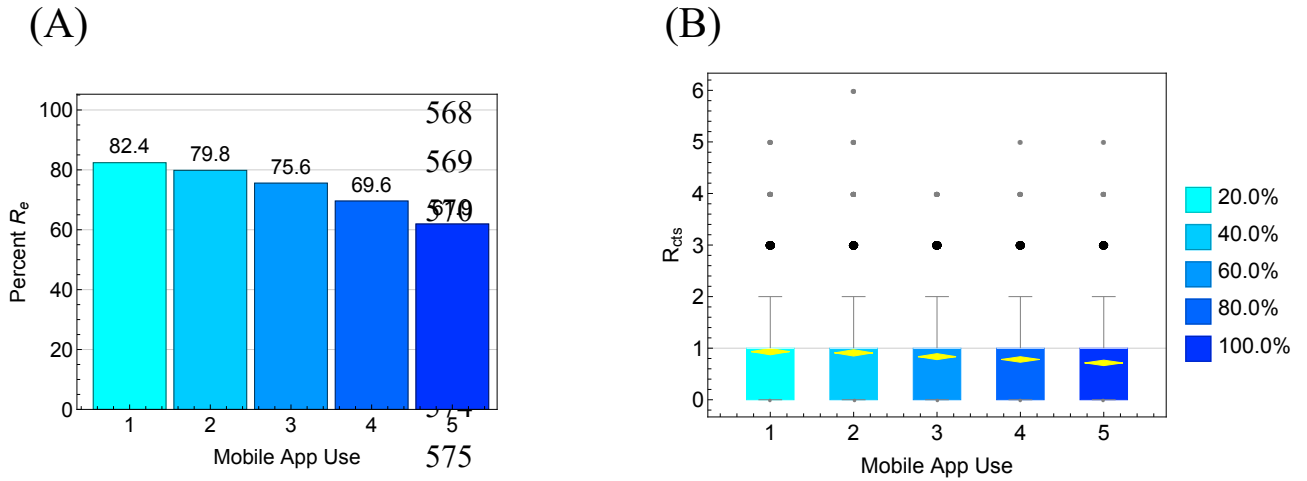551 1000 individuals and the same scenarios as in (A).

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553 (A)

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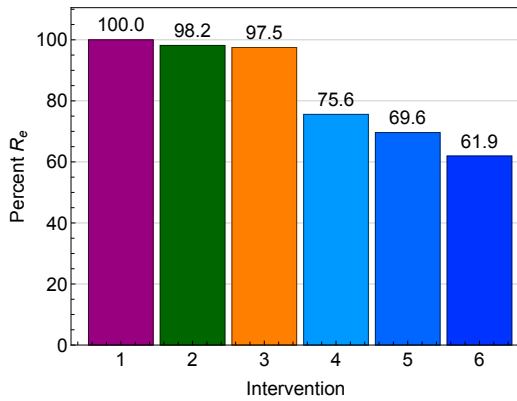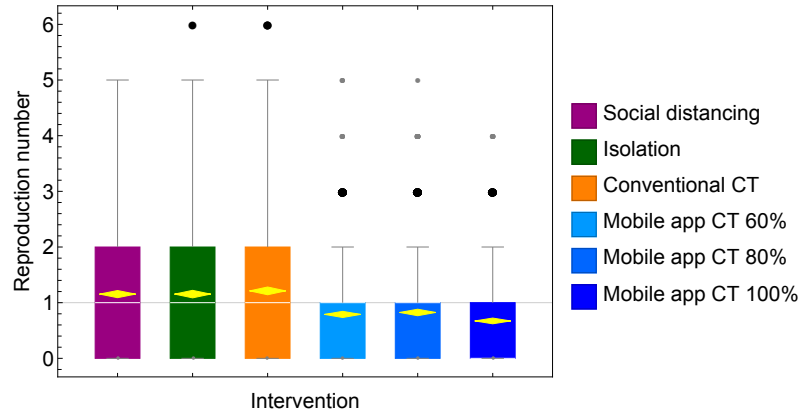
Figure 4: The impact of mobile app use on R_{cts} for varying levels of app use. In 4A and 4B, we assume that there is also testing of those who do not use the mobile app, so app use only is used for tracing contacts. In 4C and 4D, only app users, who develop symptoms, are tested. Panels A and C show percentage reductions of R_e achieved by the CTS; panels B and D show the impact of various CTS on distributions of individuals reproduction numbers.

(A)

(B)

(C)

(D)