Effectiveness of digital contact-tracing applications on COVID-19 pandemic

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ABSTRACT

UPDATE: May – June 2020. Currently, the entire globe is affected by the COVID-19 pandemic. The virus keeps spreading and governments tighten their safety measures. Many app designers have tried to develop a mobile application to execute contact-tracing more efficiently. The World Health Organization recommends a combination of measures: rapid diagnosis and immediate isolation of cases. This does not fully prevent the spread of the virus, since there are likely many cases of undetected SARS-CoV-2 infections. In order to create a higher spread prevention, several mobile applications have been proposed to the Dutch government, yet none fits the expectations. This article explores the effectiveness of such contact-tracing apps and explains how to reach the highest possible effectiveness of such applications. Ultimately it proposes recommendations as building blocks for app-developers.

CCS CONCEPTS

• **General and reference** → **Cross-computing tools and techniques**; *Verification*

KEYWORDS

ACM proceedings; SARS-CoV-2; Coronavirus; COVID-19; Effectiveness; Contact-tracing.

INTRODUCTION

The issue capturing global attention in the recent months is the COVID-19 pandemic, causing great disruption throughout the world in terms of health care and economy. Since the outbreak, many governments opted for an approach to combat the virus through limiting all social interactions within society (commonly referred to as a lockdown), putting a halt to the spread of the virus at the cost of the national economy. In the long term, this approach is not sustainable. Thus there is a need to find ways to reduce restriction on social interaction in all aspects of society without losing grip on the spread of the virus. To this end, the Dutch government has suggested the nation-wide deployment of an application designed to predict/detect persons infected with COVID-19, enabling them to accurately manage the virus' impact on society without the need for a dramatic type of lockdown. The need for such an app is still being questioned, since it entails difficulties regarding the violation of the Dutch privacy legislation. According to a study by Fraser, Riley, Anderson, and Ferguson [34], it is explained that a mobile contact-tracing app is needed to urgently support health services to control the COVID-19 transmission, target interventions, and keep people safe.

The focus of this article therefore focuses on the effectiveness of such contact-tracing apps. The objectives of the article are to determine through literary research what the relevant requirements are to the problem and what exactly the desired effect of the application is in order to meet its requirements. Finally, the objective of practical research done thereafter is to determine what type of implementation of the app satisfies the requirements set by the results from literary research.

In this article, insights on the effectiveness of digital contact-tracing applications in the context of the COVID-19 pandemic are presented. These insights lead to several recommendations on how to reach the highest possible effectiveness when discarding influence-able factors like privacy, reliability, and ethics. The state-of-the-art applications' values were reviewed together with the developers' views on their product. Simulation models were analysed to compare and give structured critique on them to conclude what could be missing in these models. Together with knowledge gained from related works, the article provides a well-structured argument.

In the related works, the current state of the art regarding technologies and apps is explored. A summary of existing technologies and their implications is discussed, which includes contact-tracing, simulation models, and current state-of-the-art mobile apps. In the results section of the article, each of these previous topics were evaluated in the context of the effectiveness of the app. With these results, a recommendation was formed for future research regarding a COVID-19 app.

It is to expect that the findings of the article entail a well-structured list on how to achieve the highest effectiveness of a digital contact-tracing application in the context of the COVID-19 pandemic. The article contributes to (i) an understanding of optimal effectiveness for digital contact-tracing apps and (ii) to the problem of designing a functional digital app in order to combat the COVID-19 pandemic, and (iii) a coherent report of relevant literature studies.

METHODOLOGY

A various number of actions and steps were taken in this research. The article is a literature review, the main sources of information can therefore be found in the related works section. In the related works section of this article, other research towards particular aspects of a contact-tracing app has been explored, among which simulation models and state-of-the-art mobile applications. Next to the explored research, a set of interviews was conducted which supported and criticized the previous explored studies and research. These interviews were conducted with two of the seven app-developers among 750 others who submitted a proposal to become the national Dutch contact-tracing app. Based on the gathered and analysed information, our view upon several aspects is given and recommendations are proposed towards the use and effectiveness of the contact-tracing app.

RELATED WORKS

In order to give clear and reliable conclusions the related works have been critically analysed to formulate results. Knowledge was gained on the following topics: effectiveness of contact-tracing; application of technology; simulation models and state-of-the-art mobile apps. This knowledge helped to focus on the critical aspects of the applications' effectiveness and create a well-structured view of what is necessary to reach this objective.

Effectiveness of contact-tracing applications

The effectiveness of contact-tracing has several coherent factors. The mobile application which would be launched should work properly to begin with. The app would therefore need to reach certain benchmarks.

One of these benchmarks is the app adoption rate [43] which the application will need to achieve. The adoption rate is the percentage of the population which is required to properly use the app in order to suppress the epidemic [38]. According to Ferretti, Wymant, Kendall, Zhao, Nurtay, Abeler-Dörner [32], if 70% of the population uses smartphones (assuming that there is no app use present for children aged under 10 and the fact that people aged over 70 have a low smartphone use). An epidemic like COVID-19 can be suppressed with 80% off all smartphone users using the digital contact-tracing app, 56% of the total population would need to download the digital contact-tracing app. Contact-tracing using smartphones can be beneficial even with a partial adoption among the population [32]. To contain the spread, the adoption rate should at least be higher than 60% [43]. The developers of the Digital Contact-Tracing System (DCTS) [24] think this percentage must be even higher: the DCTS needs a broad acceptance among the population, which would be more than 70% in order to have an impact.

The following terms will be defined as follows according to convention: R0 is the reproductive number, indicating the mean amount of infected individuals (newly infected individuals) produced by a single infector (an infectious individual) [72]. The serial interval sometimes referred to as the generation time, is the time between the infector becoming symptomatic and the infected individual becoming symptomatic [72]. The latent period is defined as the time between an individual being infected and becoming an infector [72]. The incubation period is the time between an individual being infected and becoming symptomatic [72]. Finally, the growth rate is the amount of growth in the number of confirmed infections in a set timeframe (commonly calculated per day) [72]. It is good to note that a mean incubation period greater than the mean latent period indicates pre-symptomatic transmission of the virus being a possibility of making timely intervention to stop the spread more difficult. A mean serial interval less than the mean incubation time can also suggest this is the case.

An important distinction to make is that R0 as being the measure of the spread of COVID-19 in the absence of "immunity intervention measures" (e.g. [72]) and R0 as being the measure of spread in case of these public safety measures, also noted as R(t) [84]. For instance, the official data by the Rijksinstituut voor Volksgezondheid en Milieu (RIVM) for R0 is in fact a calculation of R(t), as are many other calculations and estimations of the reproductive number based on recent data, generally collected from the year 2020 onwards (e.g. [51, 84]). This distinction is relevant for the intended purpose of a potential mobile application for combatting COVID-19 spread, in the sense that it creates a distinction between research into the viability of such an application as the sole intervention measure for containment of the virus or as one of the intervention methods. Wanting a measure of required performance when designing such an application thus requires a choice between using R0, and thus data taken from the very early stages of COVID-19 spread (previous to large scale intervention measures), or using R(t) and calculating the current reproductive number with up to date statistics (post-intervention measures). Research into the effects of the duration of the mean latent period and the average size of an individual's network within the population has been done, also enabling the first formula to be used if needed. Kiss, Green and Kao show the total number of quarantined individuals as a function of the rate of tracing (simply put for the sake of argument) and the rate of false positives in tracing for two different scenarios: one with long mean latent periods and large networks for individuals, the other with low mean latency and small numbers of average contacts per person [44]. The results derived from this indicated long mean latent periods and large networks of individuals as very influential factors negatively impacting the effectiveness of contact tracing, thus suggesting contact tracing should be used as a complementary method rather than a sole method for containing virus spread.

Firstly, before zooming into the specifics around R(t) it is important to note that quantifying R0 has as main purposes in the context of contact tracing applications to aid in identifying the necessary efficacy of the application for it to suit its purpose. Since COVID-19 is a SIR-type infection [29], indicating that individuals who have been infected and recover build up a form of immunity, calculating contact tracing efficiency is less complex since theoretically individuals that have been infected and recovered do not pose a continued risk of functioning as infected or infector. The aim for any contact tracing app is to adhere to a certain standard of efficiency which allows it to fulfil its purpose as either a sole method or complementary method for reducing R(t) to a value below 1 for the virus to eventually stop circulating. This standard is referred to as the critical tracing efficiency (CTE), the percentage of total transmissions that must be traced, and can be approximated using the value of R(t) and the mean number of contacts per individual within the population [29]. Whereas the formula using both these variables is of the form [29]:

$$tc = \frac{R0 * n(n-2) - n}{n-1}$$

(with tc being the critical tracing efficiency (CTE) and n the mean number of contacts per individual), this formula could be simplified to solely depend on R0 and give a slight underestimate of the CTE as follows [29]:

$$\frac{tc}{tc+1} \approx 1 - \frac{1}{\mathrm{R0}}$$

For instance, an R0 of 4 would mean 75% of transmissions must be traced to reduce R0 sufficiently to control and eventually stop the spread of the virus [29]. Important to note is that this is a lower bound and in practice required levels of contact tracing may be higher. Furthermore, more accurate equations take into account the factor p of contacts that are on average unknown or undetected when tracing, yielding the following formula [29]:

$$tc \approx \left(\frac{1}{1-\mathrm{p}}\right) * \left(1 - \frac{1}{\mathrm{R0}}\right)$$

Hellewell, Abbott, Gimma, Bosse, Jarvis, Russell, … and Flashe stimated that factor p to be approximately 0.10 for an R0 of 3.5 [37]. Moreover, it discusses some other relevant factors to the containment of virus spread, such as the role of the delay between symptom onset in and isolation of an individual in the population and the effect of pre-symptomatic transmission rates on the feasibility of contact tracing (particularly for an R0 of 3.5 or higher). Also, the number of false positives in contact tracing can be considered one of these several additional factors in estimations of the CTE [29, 37], albeit their level of influence on the CTE is not yet quantified to our knowledge.

By the use of these factors, a tangible standard can be set for contact tracing applications to adhere to, based on the R0 and the efficiency and accuracy of contact tracing.

Currently, there are two widely employed formulas for approximating the value of R0. Whereas both use the growth rate, one employs the value of the serial interval and the other uses the latent period and the duration of infectiousness. In [72], the formula based on the serial interval and its standard deviation was utilized to calculate R(t) (in the paper referred to as R0) as follows:

$$R(t) = e\hat{}(r\mu - \left(\frac{1}{2}\right) * r^{2\sigma^2})$$

with r being the exponential growth rate, μ being the mean serial interval and σ the standard deviation of the serial interval. The advantage of this method is in the simplification by reducing the number of variables considered. However, when modelling spread within a network comprised of clusters one cannot be certain the first symptomatic case within the cluster is, in fact, the index case for that cluster, thus factors like the latent period and duration of infectiousness become more helpful to take into consideration [72].

The second formula is the following [75]:

$$R(t) = (1 + \frac{r}{b})(1 + \frac{r}{c})$$

with b being the rate at which patients leave the latent period (exposure) and c being the rate at which patients exit the infectious stage [75]. The mathematical assumption that the rate of exiting exposed and infectious stages constant is very convenient for calculation, yet not particularly realistic [78]. The advantage of using this method is the option for expanding the formula to encompass the possibility of multiple 'types' of latent or infectious periods with their own exit rates as a mathematically equivalent and more efficient way to model non-constant leaving rates from exposed and infectious classes [78].

The statistics on the current R0 in the Netherlands released daily by the Dutch RIVM are based on the first calculation method [61]. Here a serial interval equal to 4 days is used for calculation, based on empirical data gathered by the RIVM. No additional variables or methods of approximation are mentioned [61].

These two methods are both used to calculate the R0 from data gathered in 11 different countries at the end of February and beginning of March (a total of 1155 patients from China, Japan, Singapore, South Korea, Vietnam, Germany and Malaysia) and yield more general values for epidemiological characteristics of COVID-19 useful for approximating R0 [51]. Considering combining the use of these formulas to verify the accuracy of the approximations of R0 or R(t) can thus be of significant value.

There are more relevant factors to modelling spread of COVID-19 such as asymptomatic and pre-symptomatic infection rates [32] and the relative susceptibility for infection with COVID-19 of different age groups (ABM based itself on [65] and [16] for these findings) (see Table 1).

Whenever a person has been in contact with an infected individual, the application will send a message to the possible infected individual about the situation [24]. This message should entail insights to the user and provide it with clear advice and instructions. For this method to be as effective as possible, a psychologist should be consulted about the exact wording and information of the notification, in order to achieve the desired effect [24]. This should highly increase the probability of the user succeeding in what the notification tells them, which is crucial for reducing the spread of the virus.

When looking at the effectiveness of contact-tracing, the latent period (the time interval between when an individual is infected by a pathogen and when he or she becomes capable of infecting other susceptible individuals [79]) needs to be taken into account. According to Klinkenberg, Fraser and Heesterbeek, whenever the detection time of an infected person is fixed, a larger latent period (larger than the detection time) results in a situation where every infected person is detected before transmitting the infection, so tracing need not prevent any transmission [45]. Effectiveness may, therefore, be very sensitive to the latent period, especially with little variation [45]. The sensitivity may be large in the case of single-step tracing [14, 30, 34]. This could be solved in means by introducing a variable detection time [45]. The DCTS [24] proposes to apply second-order tracing, which would include tracing down individuals who have been in contact with the notified individual. The DCTS is being evaluated together

Table 1: Infection Parameters [39]

Infection Parameters			
Symbol	Name	Description	Value
R	infectious_rate	mean number of people infected by each moderately/severely symptomatic individual	$5.75^{\times}$
A_{asym}	asymptomatic_infectious_factor	relative infection rate of asymptomatics	0.29
A_{mild}	mild_infectious_factor	relative infection rate of mild symptomatic	0.48
A_{sym}	-	relative infection rate of moderate/severe symptomatics	1
B_{home}	relative_transmission_household	relative infection rate of household interaction	2
B_{work}	relative_transmission_workplace	relative infection rate of work interaction	1
B_{random}	relative_transmission_random	relative infection rate of random interaction	1
S_{0-9}	relative_susceptibility_0_9	relative susceptibility of age group 0 - 9 to an average person	0.71^{*}
S_{10-19}	relative_susceptibility_10_19	relative susceptibility of age group 10 - 19 to an average person	0.74^{*}
S_{20-29}	relative_susceptibility_20_29	relative susceptibility of age group 20 - 29 to an average person	0.79^{*}
S_{30-39}	relative_susceptibility_30_39	relative susceptibility of age group 30 - 39 to an average person	0.87^{*}
S_{40-49}	relative_susceptibility_40_49	relative susceptibility of age group 40 - 49 to an average person	0.98^{*}
S_{50-59}	relative_susceptibility_50_59	relative susceptibility of age group 50 - 59 to an average person	1.11^{*}
S_{60-69}	relative_susceptibility_60_69	relative susceptibility of age group 60 - 69 to an average person	1.26^{*}
S_{70-79}	relative_susceptibility_70_79	relative susceptibility of age group 70 - 79 to an average person	1.45^{*}
S_{80}	relative_susceptibility_80	relative susceptibility of age group 80+ to an average person	1.66^{*}
μ_i	mean_infectious_period	the mean of the gamma probability density function for infectiousness	6 days
σ_i	sd_infectious_period	the standard deviation of the gamma probability density function for infectiousness	2.5 days
-	n_seed_infection	number of individuals randomly infected at start of simulation	5

with intervention strategies, and these results are being crosschecked using both deterministic and Monte Carlo based approach models [23]. Based on these models, applying only first-order contact-tracing might not be enough. Therefore, ContacTUM Consortium wants to enable both first and second-order tracing [24]. "Tracing second-order contacts increases significantly the number of traced potentially infected people. If every direct and indirect contact stayed in quarantine, a huge percentage of the population would be affected" [24].

Because digital contact-tracing applications are often installed on the user's mobile phone, several limitations occur [43]. Errors may occur due to the assumption that the distance can be estimated from the measured attenuation. Smartphones might share certain hardware components. Next to that, the smartphone might not be carried on the body, it could be stored in a purse, or left in the car.

Application of technology

The main focus of a digital contact-tracing application is tracing the user and collecting data on contacts within the social distancing barriers. There are several technical possibilities to realise this. The approach for highest effectiveness is being discussed together with what could be possible limitations.

Contact-tracing requires the device on which the application is installed to track the user's location, or at least, detecting every individual contact with another user. Several solutions have been proposed. Solutions included WiFi MAC address sniffing [33], GPS [24, 33, 43, 46, 52], cellular network geolocating [28, 57] and using mobile network data [24]. Due to the fact that it is supposed to work indoors as properly as outdoors, these solutions are not reliable [24]. Many believe that Bluetooth tracing is the most suitable and has also been demonstrated effective for proximity detection [15, 18]. Because Bluetooth has an effective range of around 25 metres, the use of signal strength can identify whenever another device is within the 2-metre rule according to social distancing measurements [15, 18, 82]. Therefore, many papers [1, 5, 15, 18, 21, 24, 33, 36, 40, 43, 48, 53, 64] propose the use of Bluetooth for proximity detection.

The use of Bluetooth can be split up in two main methods. Several studies propose the use of the ordinary Bluetooth, Bluetooth BR/EDR [15, 21, 36, 53], whereas others propose the use of Bluetooth Low Energy (BLE) [1, 5, 18, 24, 40, 43, 48, 64]. BLE seems to take the upper hand because of its benefits. BLE should make sure that the battery is drained by no more than 5% by performing contact-tracing, and that in a situation with 100 devices in close range [24]. The probability of the devices detecting each other successfully within 10 seconds is close to 100% [24]. In its essence, BLE is designed for continuously scanning the background [43],

TraceTogether [21] is the first example of a working digital contact-tracing application. It makes use of Bluetooth BR/EDR and shares decryption keys whenever a nearby device is located. This key will be able to decrypt an encrypted message about their infection status. Before such a message is sent, it is first delivered at the proxy servers (see Fig. 1), which is to improve the privacy of the user. This message is then sent to the person who he or she has been in contact with. The individuals who receive a message can decrypt the message by using the key they received earlier and can view the infection status of the other anonymous individual. In this case, the proxy server is added in order to preserve the privacy of the infected individuals from the government (see Fig. 1).

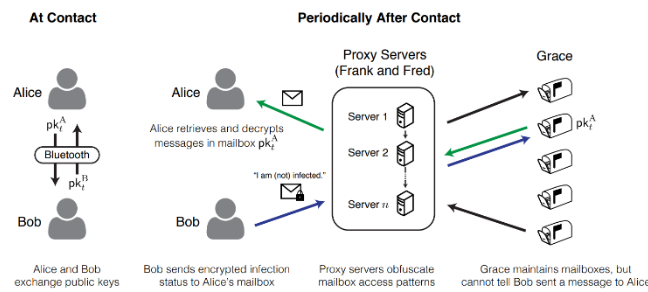

Figure 1: Overview of contact-tracing based on private messaging systems. When Alice and Bob are near each other they exchange public keys as tokens. They then periodically encrypt (using each other's public key, followed by the public keys of the proxy servers) a message indicating their infection status, and send it to the proxy server. They also periodically query the proxy server for messages posted to the mailboxes corresponding to their public keys to find out whether they have been exposed to the virus [21].

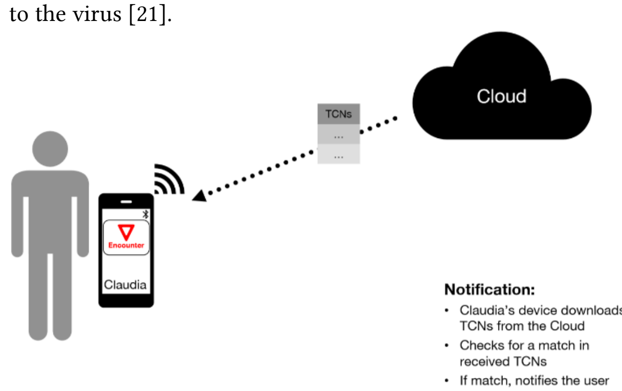

Figure 2: Overview of checking encounters. Every device can check its recorded TCNs against the reported TCNs on the server. If a device finds a match, it notifies the user [24].

ContacTUM Consortium proposes the Digital Contact-Tracing Service (DCTS) [24]. The DCTS is based on the phones emitting and scanning for Bluetooth signals, and thereby exchanging so-called Temporary Contact Tokens (TCNs) [24]. The approach uses BLE, mainly because of its continuous scanning in the background. The DCTS will activate BLE and generate a key, which it uses to generate a random TCN (the token which will be given to nearby phones). The TCN will be continuously advertised for other phones, however, it will be updated after a certain amount of time to prevent re-identification [24]. When a device spots another device's advertised TCN, it will be stored and phones will exchange their tokens. Whenever a user is confirmed infected, he or she can upload the advertised TCNs and keys to a server. This server collects all newly uploaded TCNs. When a match occurs with a TCN on the server and a stored TCN on one's device, the users will receive a notification. In order to compare the TCNs on the server with the locally stored TCNs on the device, the database from the server can be downloaded (see Fig. 2). For the DCTS to allow second-order tracing [24], the user, who gets notified because they have been in contact with an infected individual, also uploads their TCNs on the server.

ITO, a team of individuals who submitted a proposal for the Dutch national contact-tracing app, used TCNs in their app as well [41]. During the interview [41] the goal of ITO became clear, which is to create a unanimous privacy-protecting protocol that different countries and institutions can be used to build their contact-tracing apps on. At the moment of writing, the ITO team has not yet reached its goal. Things are continuously changing, and they adjust towards this. They do have a working Android app, but it is not secure yet. Within their goal privacy is their most important value. The team wants to reach this by e.g. making everything as transparent as possible. Everything is posted online, from research to source code.

The DCTS makes use of a decentralised approach [24], in order to lower the risk of re-identification of affected persons. In a decentralised approach, the personal data collected through the app is stored locally with the user. In a centralised approach, personal data is controlled by the government authority [47]. There is a strong growing trend globally, especially in Europe, which shows that the decentralised approach would be preferable [47, 50].

Bluetooth as a technology implication, however, does have several limitations. When situated in a crowded scenario where multiple phones are present, the application will use larger delays than specified in the BLE approach, which will lead to six times the energy consumption [43]. The device might need to run other Bluetooth related tasks, like wireless headphones, in parallel. Because the device can only carry out one task at a time, Bluetooth scheduling is needed [43], which limits the continuous transmission of beacons. Also, as the Bluetooth signal can potentially reach through surrounding terrain such as walls, it will identify the situation as if the individuals carrying the devices have been in close contact with each other. This could even occur though individuals are separated by a wall, which is not correct or intended.

Simulation models

A simulation model is one of the methods that is commonly used in Operational Research. Operational research (OR) deals with the application of advanced analytic models to help make better decisions. A simulation model represents the real situation that occurs in a system and tests multiple scenarios based on different behaviour [66]. Simulation models can be useful to obtain more of an understanding of a current system by testing scenarios using specific software tools [66]. It can be seen as an incorporating time that reflects any changes that occur over time [66].

Because of the COVID-19 pandemic, the government has to come up with a set of policies to contain the virus. Multiple simulation models are used to see what effect certain policies have on society. The mobile contact-tracing app is one of these policies which can be tested with the simulation models.

Figure 3: ASSOCC user interface. The user interface depicting houses, workplaces, hospitals, schools, station, and people's movements [12].

The ASSOCC model (Agent-based Social Simulation for the COVID-19 Crisis), is a simulation model that has specifically been designed and implemented by European researchers from Umeå University, TU Delft, Malmö University, Utrecht University, Caen University and Stockholm University to address the societal challenges of the COVID-19 pandemic [12]. This model studies the individual and social reactions to containment policies and it is a tool that can be used by decision-makers (such as the government) to explore the different scenarios with their effects. The ASSOCC model does not generate predictions, however, it simulates the behaviour of a synthetic population given a set of policies (for example the contact-tracing app) [12]. The model enables to study the possible effects on the spread of the virus, how people can be expected to react to the policies, and the socio-economic effects of the policies [12]. ASSOCC is built-in NetLogo (see Fig. 3), which is a multi-agent programmable modelling environment [80]. It is based on a set of artificial individuals which each have a set of given needs, attitude towards regulations and risks, and demographic characters [12]. Each artificial individual decides at each time what it should be doing. These decisions are based on the individual's profile, state and social, psychological and physical needs [12]. An action is selected by an individual by first making a list of all possible places it can go to with different motivations, which is called an action [12]. It then calculates the global expected effects on the needs of these actions and it lastly selects the action which satisfies the highest number of needs [12].

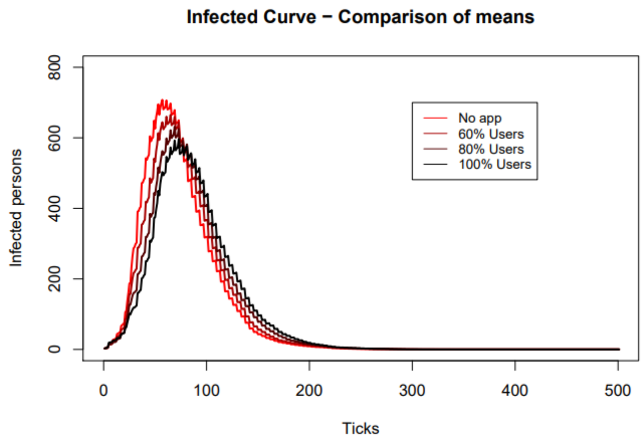

Figure 4: Infected Curve – Comparison of means (01). Impact of app use on number of infected agents. [11].

The ASSOCC model has looked at the effects of implementing the contact-tracing app policy into society. In this scenario, a perfect app aligned with all functional, legal and ethical requirements is assumed [11]. The effectiveness of such an app was researched by performing three experiments. First, the effect of the app depending on different percentages of the population (0%, 60%, 80% or 100%) using the app was studied. According to the ASSOCC model, using the app does result in a lower infection peak (see Fig. 4), however, these differences are not significant and the increase of app users results in a sharp increase of tests needed (see Fig. 5) [11].

Next, the effect of using the app was compared with random studies of a percentage (0% or 20%) of the population. According to the ASSOCC model, random testing raised the awareness of infection, even when the artificial individuals had no reason to suspect infection and is more effective than the app (see Fig. 6 & 7) [11].

Third, the effect of the app depending on the percentage of risk-avoiding individuals that use the app (0%, 30% or 60%) was studied. According to the ASSOCC model, the effects of risk-averse people were not significantly visible (see Fig. 8) [11].

The developers from the ASSOCC model concluded that the effectiveness of contact-tracing apps on lowering the rate of infected individuals is limited and lower than that of random testing and that the app makes no significant contribution to the spread of the virus [11].

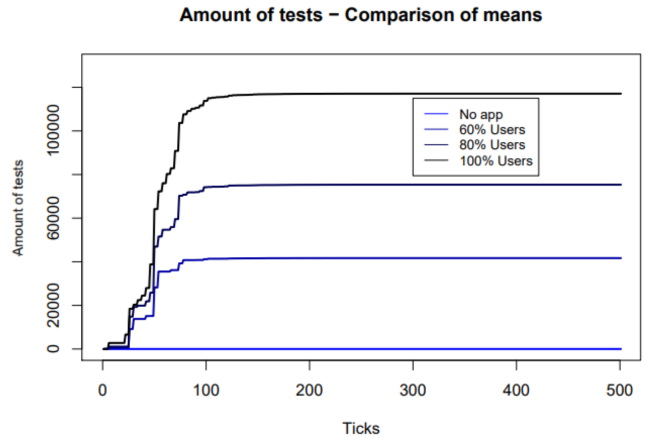

Figure 5: Amount of tests – Comparison of means (01). Amount of agents to be tested under different app use configurations [11].

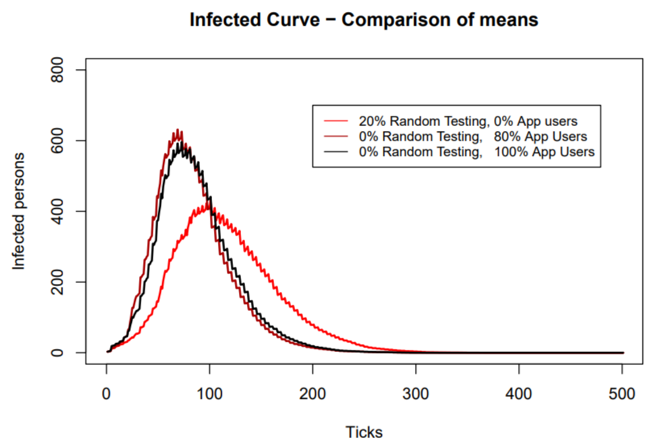

Figure 6: Infected Curve – Comparison of means (02). Comparing app use with random testing [11].

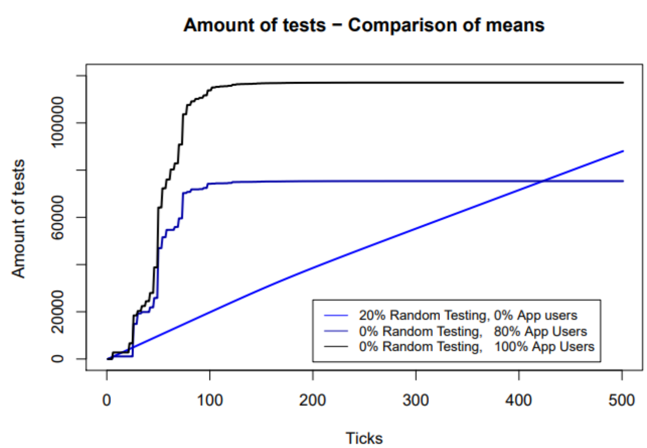

Figure 7: Amount of tests – Comparison of means (02). Amount of tests under different conditions. [11].

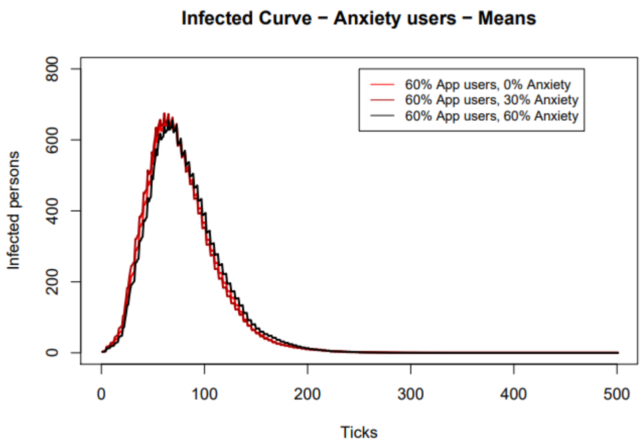

Figure 8: Infected Curve – Anxiety users - Means. Influence of risk averse agents. [11].

The Dutch government based their decision of implementing a contact-tracing app on the COVID-19 agent-based model (ABM) with instantaneous contact-tracing [39]. It was developed to simulate the spread of COVID-19 in a city, and to analyse the effect of passive and active policies [39]. The demographics of this model are based upon UK national data for 2018 from the Office of National Statistics [39]. The ABM model is based on a set of artificial individuals which are categorized into nine age groups by decade. Each individual is part of a structural and transient network and is part of a household, which is an important part of their daily activities. Every day, each individual interacts with a random subset of their connections and has random connections. The status of the infector, the susceptibility of the infected person to infection according to age and the type of interaction determine the rate of transmission of the virus [39].

The active policy of digital contact-tracing was studied in this model. With contact-tracing, a random number of interactions is assigned to the model. The usage of the app is just like the model age-dependent. According to the ABM, contact-tracing is vital to control the spread of COVID-19 for infections with high levels of pre-symptomatic transmission [39]. The ABM allows to explore this policy and its effects and contains the option for recursive tracing of contacts of contacts [39].

Both the ASSOCC model and the ABM are agent-based simulations. This means they are both able to cope with the uncertainty and variability of the system [12]. Both models are however constructed differently, which leads to different results of the effectiveness of a contact-tracing app. In this article, these two models were analysed and compared to each other to give advice about the effectiveness of contact-tracing apps.

State-of-the-art mobile apps

Many countries have researched and possibly applied a contact-tracing application that will help to decrease the spread of the virus. State-of-the-art mobile apps have been explored in this article. The following applications discussed are purely selected on relevant technologies, which are most likely to be effective. This mainly results in applications which make use of Bluetooth. Because this article can be used by app-developers based in the same culture and context as the Netherlands, it is only relevant to discuss applications which are applied in the same culture and context as in the Netherlands, or any applications which have nationally been deployed and share their data. Many countries have their own applications as well, however, much information is withheld, or human rights are violated with the use of these apps [56].

Singapore was the first country to implement a Bluetooth contact-tracing app. This first major Bluetooth contact-tracing app that eventually became available worldwide is TraceTogether [21, 56]. It was released on March 20th 2020 by the city-state and was not made obligated to download. One-week later Singapore made it freely available for developers worldwide [22]. Even though the app was not obligated to be downloaded, the country's development minister, Lawrence Wong, told local media that "In order for TraceTogether to be effective, we need something like three-quarters—if not everyone—of the population to have it" [27]. In the beginning, when the app was released, it looked promising for Singapore to reach this adoption rate. In the first 24 hours that the app was released, it had been downloaded over 500.000 times [22]. However, at this point, less than 25% of their citizens had downloaded the app [13]. Therefore, TraceTogether has not been proven very effective. However, because Singapore was the first country to implement a contact-tracing application for the COVID-19 pandemic, errors occurred during the implementation of the app. The two main problems were the privacy concerns and a technical problem regarding Bluetooth. The use of the app raises many privacy concerns. These concerns mainly include the storage of data and whether the app tracks the user's location. Individuals would feel watched when using the app. Due to the negative portrayal and highlighting the privacy concerns of the app in the media, Singaporean citizens became sceptical towards the app. French security researcher Baptiste Robert [55] looked at the technical details behind Singapore's app. Although the app has privacy concerns, TraceTogether is a very good example of not getting a national adaptation. "The nature of the app is why people didn't download it. People don't understand the technical details behind the app, they just understand 'the government wants to trace me'" [55]. The individuals who did download the app experienced technical difficulties when using it [17]. The way of communication, Bluetooth, caused problems since people used different brands of mobile phones. The major problem had to do with Apple. iOS rules usually prevent third-party apps from running in the background and broadcasting Bluetooth signals [17].

Australia implemented a contact-tracing app as well. Although there were privacy concerns, the government released the COVID Safe app on the 26th of April, 2020. Their app is based on the source code of the TraceTogether [21] app from Singapore. Together with the app's release, the government published a privacy impact assessment, and stated the source code will be released as well. The Australian government does not obligate Australian citizens to download the app [60]. Health Minister Greg Hunt stated the government's target for the uptake of the app is 40% of the population in order to ease some restrictions in states and territories [67]. After four weeks no official numbers have been released but based on estimations of the number of Australians with smartphones, it is now about 1.5 million under that target [67]. In four weeks the app has gone from being the key to freedoms to an add-on to existing contact-tracing methods. Although Australia had the benefit of knowing what errors TraceTogether suffered from, together with Greg Hunt stating that they have "been able to work to ensure that that is not an issue in Australia", the COVID Safe app suffered the same technical issues regarding iPhones [67]. The applicable solution to this problem for both Singapore and Australia is probably to use the Apple-Google API [6, 4]. The Australian government is currently evaluating this, but according to a Melbourne cryptographer, Vanessa Teague, it would require a major overhaul to the app [67]. Recently, Apple and Google have been working together to fix the technical problems and making technology, the mentioned API, that is available for governments to use for their contact-tracing apps [4].

Not many European countries have succeeded in launching a contact-tracing app yet. Only two countries did: Austria and Switzerland. Austria was the first country from the European Union to implement a contact-tracing App. The Stopp Corona app works with the Decentralized Privacy-Preserving Proximity Tracing technology (DP3T) [28] and was released on March 25, 2020. Within a week it had been downloaded over 100.000 times [71]. Although it has been released earlier than the Australian app, no results of effectiveness have been made public. There is a possibility that applications which use DP3T technology also had similar problems with Bluetooth as the other mentioned apps, but this has not been reported yet. However, Austria is planning to make use of the Apple and Google API in combination with DP3T in its Stopp Corona app [19].

The second contact-tracing app in Europe is the first app which is released that makes use of the Apple and Google API. The SwissCOVID app in Switzerland has been released on the 26th of May, 2020. The application is currently in a test phase and is only available for members of the Swiss army, hospital workers and civil servants. Due to its recent launch, not much information about the app can be found.

Next to Switzerland, several other countries are or have performed trials and/or pilots of other contact-tracing applications. Finland has trailed contact-tracing app Ketju in the Vaasa Central Hospital. The app also makes use of DP3T technology [3, 28]. The app would need improvements according to critique, however, these necessary amendments cannot be implemented earlier than August [69].

The Deus initiative, one of the interviewed app developers, proposed the DP3T protocol as well as the best option to implement in the Dutch national contact-tracing app [70]. Their reason for this was because this protocol does not save personal information neither location. During a technical audit, they concluded that this protocol best guarantees privacy. However, at the same time, it is a big disadvantage because the GGD, the Dutch Health Service, would want to know this information. Another important aspect of proposing this protocol is the fact that it is open source. Deus thinks when it is developed by a community it can eventually be developed to a European Standard of a track and trace app.

The United Kingdom has decided to develop their own app which had been set for a pilot in the Isle of Wight region of England. This app is central to the new track and trace phase that the UK has moved in to [73]. During this pilot, the streets on the Isle of Wight seemed to be busier than in previous weeks. Whether this is because of the better weather than in the previous weeks, or because people think they can because they are using the app is unclear [58]. However, a scenario in the supermarket supports the latter. Someone was reprimanded in the supermarket for not observing social distancing. They justified it saying: "It's OK, we've got the app now" [58].

RESULTS

Effectiveness of contact-tracing applications

In order for the application to be effective, a certain percentage of the population needs to use the application. Taking the study of Ferretti, et al. [32] and Kindt, Chakraborty and Chakraborty [43] into account, an adoption rate of at least 60% of the total population is needed in order to prevent transmission. This percentage stays at the same value, even when the reliability of contact-tracing detection is 100% [32]. In the Netherlands, 87% of the population (individuals above the age of 12) uses a smartphone in 2018 [8]. This would lead to at least 68% of all smartphone users in the Netherlands to use the app. When deploying the contact-tracing application in the Netherlands, the adoption rate should be easier to reach than in countries where the smartphone use among the total population is lower.

In the absence of empirical data for approximating several epidemiological characteristics (such as the duration of the latent period and duration of infectiousness) of the spread of COVID-19 in the Netherlands specifically, we will limit ourselves to the employment of the first formula for estimating R(t) like the RIVM, using only the serial interval.

According to Dutch authorities from May 29th 2020 up to June 8th 2020 (a 10 day period) the number of new cases of COVID-19 was 1312 [54]. After the 7th of June, 2020 the total number of confirmed cases was 47,574 [54]. Thus the growth factor over 10 days was approximately 1.028, resulting in a hypothetical growth rate of 0.0028 per day. Since for both statistics on West-European countries and the Netherlands, in particular, the mean generation time was evaluated to 4 days [61, 84], we will use this in our calculation of R(t) along with the standard deviation of 2.4 days from the mean serial interval [84]. This yields an R(t) of 1.01 (95% CI: 0.99 − 1.03) (using the sample size as used in [84]). Due to R(t) being so close to 1, the related CTE derived from this would be very small, indicating a lack of use for employing a contact tracing application with the current intervention measures in place.

Calculating the CTE using:

$$\frac{tc}{tc+1} \approx 1 - \frac{1}{1.01}$$

would yield a CTE of 2.0%. For the sake of argument, assume that p with R(t) = 1.01 is fivefold that of p with R(t) = 3.5, using:

$$tc \approx \left(\frac{1}{1-0.5}\right) * (1 - \frac{1}{1.01})$$

would still yield a CTE of 3.9%. Therefore, even if one assumes the value of p increases dramatically as R0 decreases, for which there is no solid basis at all, it still results in a CTE that signals a lack of need for a contact tracing application at this point in time in Dutch society. However, past research indicates higher values of R(t) by a large margin, with or without little social distancing measures in place. Hence, this does not indicate in any way a contact tracing app does not have added value in the future [2].

There is no shortage of alternatives to these values used above, however, these values are derived from data within specific contexts and are thus not necessarily indicative of the situation within Western-Europe and the Netherlands specifically (the research is predominantly based on data from China and other East-Asian countries). Still, they can at least be valuable to use as an indication of what epidemiological characteristics to expect of COVID-19 in a certain context (e.g. [2, 16, 49, 65], taking into account culture and immunity intervention measures in place at that stage of the outbreak). Lastly, due to the risk of a resurgence of the large scale spread of COVID-19 in case of lifting the social distancing measures as discussed in [2], this data irrelevant for the approximation of R(t) in Western-Europe now might be a better indicator for future values of R(t) than the ones currently measured.

To summarize, calculations of R(t) and the CTE show that there is no immediate need for a contact tracing application of any sort. However, since measures to mitigate COVID-19 spread are slowly being retracted there is good reason to assume value in the development of such an app for use in the future. The plethora of sources for empirical data on COVID-19's characteristics does beg the question of whether all data is suitable for one specific society with a specific culture and set of intervention measures against virus spread. Researching applicability of data and collaboration with the RIVM for developing a corona app for the Netherlands is advisable.

In order for the infected individuals to take action, a message should be sent to them including the information about the situation. In order to achieve the highest amount of effectiveness of this message, a psychologist should be consulted about the exact wording and information of the notification [24]. This will result in a higher probability of the infected individual following the measures.

The best possible solution to solve the limitation that the individual will not always take their phone with them is to propose a new device which can be worn on the body [43], to prevent the signal from being left in the car for example.

In order for the app to reach the highest amount of infected people, suggested is the use of second-order tracing. This results in a high percentage of the population who would be affected and contacted in case of possible infection [24], and thereby increase the effectiveness tremendously.

Technology application

The type of technology that is used for a contact-tracing app, can be of importance for the effectiveness of the working of such an app, as well as for other factors that could influence the effectiveness.

For contact-tracing, solutions such as Wi-Fi MAC address sniffing, GPS, and cellular network geolocating have all been proposed. However, the most suitable for use in CTA is often believed to be Bluetooth tracing. Many point to the effectiveness of proximity detection, that has already been demonstrated [15, 18]. It is also claimed that while Bluetooth has an effective range of around 25-30 metres, signal strength can be used to effectively identify whether another device is within the 1,5-metre rule promoted as a component of social distancing [53].

The original Bluetooth BR/EDR protocol was designed for primarily "pairing" phones with other devices such as computers, Bluetooth speakers, or keyboards. It had the purpose of data communication and was a non-time sensitive process. It was not designed to have a reliable and sustainable contact-tracing, as what currently is looked into as a solution for this pandemic. In the traditional pairing process, if the pairing is not successful then the user has to reset one of the devices and try again. This manual intervention is not sustainable in the context of contact-tracing, where two or more phones are always expected to "pair" reliably.

In comparison, the Bluetooth Low Energy (BLE) protocol, has been designed for continuously scanning in the background and is, therefore, the main choice for proximity tracing on smartphones. The main reason why contact-tracing apps choose for continual transmission and listening instead of continuous is energy [43]. The energy costs would be higher when using continuous transmission and listening.

In order to cope with the fact that several devices can use the Bluetooth signal, Bluetooth scheduling will need to take place [43].

There is however another problem that arises with the use of BLE. It can namely travel through a wall, just like any other Bluetooth signal. Even though the more objects there are in between the devices, the less overall range a device will have [68], it can lead to some troubling scenarios.

One of these scenarios is tracing through your neighbour's wall. Imagine your neighbour, who you do not come in contact with, tests positive for the virus. Both phones, yours and theirs, connect with each other via Bluetooth through the wall (false-positive contact detection), it can lead to possible quarantine for you, even though you have not come in contact with each other. This leads to some problems especially in heavily populated areas, such as in cities and apartment complexes.

One solution which this article proposes, would be the use of sound or sonar technology in combination with this BLE. While the BLE detects the phones at a continuous pace, the sound application could act as a safety switch to check whether there is an object such as a wall in between both phones. SONAR-X [20] claims to be more accurate than BLE due to fewer false-positives. Their technology could be combined with the reliability of BLE and lead to an even more reliable solution.

For a contact-tracing app, there is a choice between handling with a centralized or a decentralized approach. In a centralized approach, the government authority will control personal data. With a decentralized approach, the collected data will be stored locally with the user [47]. The choice regarding the use of a centralized or decentralized approach lies mainly within the arguments regarding data protection and privacy.

With centralized structures, the collected data of the app is controlled by government authority. Centralized apps follow mainly the PEPP-PT (Pan-European Privacy-Preserving Proximity Tracing) [25, 57], but this framework is according to the technical community too academic for practical development. A decentralized structure has the data enclosed or controlled by individuals on only personal devices. Those apps follow DP-3T (Decentralised Privacy-Preserving Proximity Tracing) [28, 35], but this is only partly decentralized. No pooled data is collected, which largely mitigates privacy risk. The non-infected individuals' data are decentralised based, and the infected individuals' information will be collected anonymously to a central database [47]. Google and Apple will release an exclusive decentralized framework which will be more compatible with IOS and Android systems [7].

There would be a trade-off between the insights gained and the privacy of the data. The decentralised and no GPS solution gives one of the highest levels of data protection for users because no personal data is collected unless the individual is infected with the virus. Apps cannot collect the movements and trace them geographically without GPS tracking. This means that the data can't be traced to an individual. Bluetooth tracing does work as compatible technology for this decentralized approach. However, this means that data collected cannot be driven into a centralized database for analysis and the government has less information for controlling the self-quarantine and movement of the disease [47]. This, however, does not mean the effectiveness would go down as a result. Decentralised systems are capable of providing data to epidemiologists to understand the disease [50], who in their turn can give an informed opinion or advice to the government.

In conclusion, a decentralized approach would fit well regarding data issues and be more compatible with a Bluetooth based system, and is used in the simulation models analysed. This together with the fact that there is a strongly growing trend globally, and especially in Europe, which shows that the decentralised approach would be preferable, while not compromising the effectiveness of a system [47, 50].

Simulation model comparison

In this section, important aspects of the ASSOCC model and the ABM are compared to each other. The ASSOCC model and the ABM differ from each other and both give different results on the effectivity of contact-tracing apps. According to the ASSOCC model [31], the contact-tracing apps are not effective considering the containment of the virus. According to the ABM [39] the contact-tracing apps are effective considering the containment of the virus. Because of these differences, their use might lead to a false feeling of security which ultimately can contribute to a second wave of the contagion [26]. Therefore, it is important to compare these models and find out why they lead to different results. The AMB is based on large scale mathematical models of epidemics, while the ASSOCC model is based on human behavior combined with models of epidemics [26].

The major differences between the ASSOCC model and the ABM are related to specific properties of the COVID-19 virus. The first property occurs in the time between becoming infected and showing symptoms [26]. This time is quite long. In the ABM this time is called 'T_{sym}'. It is drawn from gamma-distributed variables of the time taken to make the transition [39]. This gamma distribution creates different values that are given to a parameter. Infectiousness starts at zero. This is the moment someone gets infected (T = 0). It then reaches a peak at some intermediate time and goes back to zero when one is not infected anymore. To see how many interactions individuals have, together with which other individuals, a mathematical model is used in the ABM which divides the interactions uniformly or normally over all possibilities [26]. These mathematical models do relatively well in 'normal' situations, but in crisis situations, people behave differently and do not behave according to expectations [26]. This does not disturb the results of the model when the interval in which this happens is short. However, when the interval gets longer, the mathematical model used in the ABM is no longer viable. Besides the ABM, this is also seen in macroeconomic models wherein a 'normal' situation the model works fine, but in a crisis situation like the COVID-19 virus individuals do not behave as expected and the deviations become too great to make these models viable [26]. The AMB currently does not have data on the distribution of the duration of interactions. The effect of this on the transmission is thus not modelled here. The ASSOCC model does not model this either. In the ASSOCC model for infection, the following states are implemented. For infection, the days between transition into asymptomatic contagiousness is 2. For Asymptomatic contagiousness, the days between transition into symptomatic contagiousness is 4. The agent's transition into the next state is given by these numbers of days. So, the time between infection and showing symptoms in this model is 6 days (2 + 4). These numbers are based on theories from sociology that describe individual behavior as a result of a combination of basic values, motives and affordances over many contexts [12]. Different parameters are introduced into the system to properly represent the distribution of the disease. In this example, it is clearly seen that the ABM is based on mathematical models (gamma distribution) and the ASSOCC model is based on behavioral models.

The second property contains the skewed age distribution of the COVID-19 infection [26]. Young people have a lower chance of getting infected, but when infected they mostly do not show symptoms and are thus asymptomatic. Asymptomatic means that they are infected with the virus without showing any symptoms and thus without knowing they are carrying the virus. Because of this they are most likely not being tested and continue to distribute the virus. In general, young people also relatively meet more other young people. Considering this, it is likely that the virus can spread for quite some time without it being noticed [26]. When looking at contact-tracing apps, there are a lot of contact points, along which the virus is still spreading, despite the usage of an app. Both models distributed the individuals differently and based the corresponding values on different studies. The individuals in the ABM are categorized into nine age groups by decade, from age group (0-9 years) to (80+ years) [39]. The population of these age groups are given a value. These values are based on the age-stratified population of the UK and the number of households containing n people (with n = 1, 2, ..6,) provided by the 2011 Census by the ONS [39]. The values match the OpenABM-COVID-19 baseline parameters [39]. In the ABM there is also looked at the daily interactions age groups have in their households. Children (0-19 years), for example, have more interactions in their households than the elderly (70+ years). The value of interactions in a household also matches the OpenABM-COVID19 baseline parameters. The values are acquired from empirical estimates [39]. In other words, a previous study of social contacts for infectious disease modelling is used to estimate the mean number of interactions individuals have by age group. The previous study used in the ABM model is based on participants being asked to recall their interactions over the past day [39]. The values given to each age group for the number of interactions at workplaces and at random places also match the OpenABM-COVID-19 baseline parameters. The mean numbers of the connections an individual has were chosen so that the total number of daily activities matched that from the previous study of social interaction [39]. In the ABM the rate of transmission is determined by three factors, of which one is the age. To model the susceptibility to infection of a contact according to their age the ABM refers to literature where close contacts of confirmed cases were monitored and tested [39]. The number of tested individuals and the number of positive results were reported within each age group. The ratio of the positive results to the number of tested individuals was defined per-age to calculate the attack rate [39]. Then, a fraction was made of close contacts of a confirmed infected case. Next, data was merged from different references, the polynomial form to the proportion in each age group was then fit to the 'midpoint' of this attack rate, and a final normalization factor was defined [39]. This defined the values for a contact according to their age. These values again match the OpenABM-Vovid-19 baseline parameters. Considering infection, an individual in the ABM enters a disease progression cascade in which the outcome and rates of progression depend on the age of the infected person [39]. The age variables in this disease progression cascade are the probability of transition to a particular state when there is a choice, where the probability depends upon the age of the individual [39]. Simulating contact-tracing in the ABM considers that the app uptake is age-dependent based on smartphone ownership data. In the ASSOCC model it is just like the ABM considering that different ages have different chances of infecting others. The individuals in the ASSOCC model are categorized into 4 groups. The first group is called “youth”, which refers to children, the second group is called “student”, which refers to university students, the third group is called “worker”, which refers to adults, and the last group is called “retired”, which refers to elderly. The aim is to use 300 agents in the simulation. In this model, there are four types of households. These are, adults rooming together, retired couple, family and multi-generational living. The distributing of individuals among these households is based on the UN report “Household Size and Composition Around the World 2017” [31]. In order to determine whether an individual will get infected, the propagation risk is multiplied by a factor that represents the density of the gathering point they are currently at [31]. Depending on the category of age group an individual belongs to, agents perform different practices. Children for example only go to school and home in the ASSOCC model. Each individual is given a different set of values, including their personality and culture [31]. This personality includes whether individuals are for example risk-avoidant and keep their social distance even when the chance of getting infected is low [31]. Therefore, a decision between the following implementation has been made: “the preparedness for obeying the rules and when not obeying, actively looking for crowds” [31]. Furthermore, individuals of different ages have a different chance of infecting others in the ASSOCC model. The elderly are affected very heavily in this model. In both the ABM and the ASSOCC model, statistical data is used to initialize the age of the individuals and the household settings [31].

The third property contains the demographics and living arrangements [26]. Considering the virus, these are determining factors. The results in different countries are for example different. The two models deal with the demographics and living arrangement differently. The ABM does not include migration in its model. However, the ASSOCC model does include this in its model to model the effects of travelling. This allows individuals to travel abroad and transfer the virus from there. It includes a probability of an individual going abroad, a probability of an individual getting infected when being abroad, a probability of an individual coming back when being abroad, and a risk of getting infected when travelling locally (within the city) [31]. In the ABM each individual has a household, workplace and random network. Each individual interacts with a random subset (50%) of their connections on their workplace network [39]. For children, the workplace network is the school they are going to. On each of the ‘school’ network, a small number of adults is introduced in the network to represent the teachers and other school staff [39]. The elderly have separate networks representing day-time social activities among other elderly individuals. The demographics of the ABM are based upon UK national data from 2018 from the Office of National Statistics (ONS) [39]. Individuals are as said before categorized into nine groups by decade in this model, and each individual part of a household. The living arrangements of individuals in the ABM is based on the ONS as well. The ASSOCC model is based on a set of artificial individuals, each with given needs, demographic characteristics, and attitude towards regulation and risks [12]. This demographic characteristic includes the general profile (age, home, health), the sociality profile (social groups, conformance, sociality, social distance, and risk avoidance), available actions (work, stay home, shop, ...), epistemic model (infected, not infected), and the state (virus state, home, social groups) [9]. In the ASSOCC model, there are four living arrangements. These are, adults rooming together, retired couple, family and multi-generational living. The distributing of individuals among these households is based on the UN report “Household Size and Composition Around the World 2017” [31].

Both the ASSOCC model and the ABM have not implemented the impact hospitals have on the pandemic. This impact is large, as the clinical outcome of infection depends on the access to good hospital care [39]. The models should contain more details about the transmission within hospitals and patient flows.

To conclude, considering the first property, which is the time between becoming infected and showing symptoms, the ABM draws this time from a gamma distribution, while the ASSOCC model based this time on theories from sociology. Within the first property, it becomes clear that the ABM is a mathematical model, which does not do well in crisis situations like the COVID-19 pandemic. The ASSOCC model is on the other hand based on behavioral models, which can perform well in a crisis situation. Considering the second property, which is the skewed age distribution, the ABM divides the population into nine groups by decade, while the ASSOCC model divides the population into four groups (youth, student, worker, retired). The values of the population in the ABM are based on an age-stratified population of the UK. The values of the population in the ASSOCC model are based on the UN report. Statistical data is thus used in both models to initialize the age of individuals. Considering the third property, which is the demographics and living arrangements of individuals, The ABM does not include migration, while the ASSOCC model does include migration. Migration should be concluded, as the COVID-19 pandemic affects travelling. The demographics of the ABM are based on the ONS, and the demographics of the ASSOCC model are based on the UN report. Furthermore, the living arrangements in the ABM are households of which the values are based on the ONS. The living arrangements in the ASSOCC model are adults rooming together, retired couples, families and multigenerational livings, of which the values are based on the UN report. Statistical data is again used in both models to initialize the demographics and living arrangements of individuals. The three properties are not easy to capture in the ABM, as this is a macro-level model. In Macro models, individuals are considered to behave similarly and aggregate across large population numbers. It is therefore difficult for the ABM to identify specific and different behaviors. “It is similar to say that everybody in the Netherlands is 42,6 years because that is the median age for the whole Dutch population.” [26] The ABM model does consider differences between an individuals’ age and living situation, but that is not enough. In contrary, the ASSOCC model considers the differences between the age of individuals, their living situation, backgrounds and behavioral motives. This helps to identify the possible differences across the individuals and how the contact-tracing apps can be expected to be used given the characteristics of a specific group [26].

Simulation model additions

One possible expansion on the simulation model(s) for the spread of COVID-19 existing presently involves modelling nosocomial transmission, the spread of the virus within medical institutions. There exist plans for modelling possible nosocomial transmissions in a set of interactions between patients and staff. This is due to the large impact of the outbreak on medical facilities and the dependence of treatment of infection on good healthcare [39].

These types of interactions patients or contacts of patients infected with COVID-19 may have with medical staff in a hospital setting have been categorized into two levels of contact with their respective degree of risk: close/high- to medium-risk contact and casual-/low-risk contacts [31]. These categorizations narrowly match those utilized in the Dutch healthcare system [63], indicating procedures are at least in place to somewhat alleviate the threat of nosocomial transmissions.

Data from the early stages of the outbreak (January 2020) suggests possibly roughly 40% of the COVID-19 transmissions were hospital-associated, asserting the likelihood of added value to the simulation models to model this aspect of COVID-19 spread [76]. Furthermore, 26% of patients required admission to the ICU [76]. Another retrospective study [77] showed how a sample of 1716 health workers was infected together formed 3.84% of the total number of COVID-19 patients at that point in time (end of January, 2020). Reportedly “the nosocomial infections extremely burdened the health system and hindered early infected individuals from getting immediate medical supports, therefore resulting in high case-fatality rate in Wuhan” [77]. However, as seen in the SARS outbreak, personal protective equipment (PPE) has demonstrated to be effective in the reduction of nosocomial transmission, evident from more recent statistics on the subject (from March, 2020). Using the categories of contact [31], a study in a hospital in Hong Kong found that after 28-day surveillance of a hospitalized COVID-19 patient, the 10 patients and 7 staff members that had been in ‘close contact’ with the patient tested negative for COVID-19, suggesting PPE is in fact very effective in preventing nosocomial transmission [81].

For an increased insight in the possible situation regarding nosocomial transmission in Western-Europe, it is advantageous to specify what type of interactions between medical staff and patients yield risk of transmission of the virus. Multiple findings suggest that transmission is in fact not through an airborne route, but through droplets of bodily fluid. Implying transmission can be prevented by basic infection containment measures, such as wearing surgical masks and having a good hand and environmental hygiene [81, 59].

Several respiratory treatments for very ill patients are regarded as “high-risk factors for nosocomial transmission” among which are the following: intubation, manual ventilation by resuscitator, non-invasive ventilation (NIV), a high-flow nasal cannula (HFNC) and patient transportation [68]. Reports suggest that NIV and HFNC were used for somewhere between one third and two-thirds of COVID-19 patients admitted to the ICU. There is a suspected connection between aerosol generation by these devices and transmission of the virus [59]. Even still, some epidemiological statistics show that NIV was in some form associated with the nosocomial transmission of SARS, thus suggesting the same be true for COVID-19 due to the characteristics these viruses share (no such statistics exist for HFNC) [59]. Due to such findings, concerns for transmission within the same room stay, “especially when aerosol-generating procedures are performed”. Therefore, measures like masks using HEPA filters could provide extra protection, mainly for non-intubated patients [59].

Insights into exact procedure within Dutch medical facilities and on the ICU for treating COVID-19 patients is lacking. Thus conclusions on the current state of nosocomial transmission of COVID-19 within Dutch healthcare are difficult to draw. More information from the “Landelijke Coördinatie Infectieziektebestrijding” (LCI) department of the RIVM on statistics concerning the use (procedure and frequency) of these aerosol-generating procedures would lead to a better understanding enabling modelling of the simulation. Also, if in the future the epidemiological report by the RIVM [62] would include statistics on the nosocomial transmission rate, this would render modelling this aspect of the spread of COVID-19 very feasible.

Other areas of healthcare, such as mental health institutions could be more prone to serving as a medium for the transmission of the virus. Recent studies show that mental health care is much needed due to the level of pressure put on the medical staff, particularly ones working at the ICU [83]. In the coming period, mental health care facilities will treat more patients with increased risk of being infected with COVID-19 due to their increased exposure to and contact with COVID-19 patients. Also, institutions such as psychiatric hospitals [86] and nursing homes [62] are prone to facilitating the spread of the virus. Modelling these facilities within society using the latest statistics on the risk of transmission of COVID-19 with interactions taking place in these facilities would benefit a more accurate simulation predicting the spread of the virus within society.

In summary, focussing resources on developing simulation models that reflect the spread of COVID-19 within hospitals, mental health care facilities and nursing homes could increase the accuracy of existing models. Contacting the RIVM for specific data on the nosocomial transmission of the virus or for information about the procedure with PPE and aerosol-producing treatments is advisable.

State-of-the-art applications

A various number of contact-tracing apps and pilot studies and their results, if there are any, have been discussed. But what do these results mean for the effectivity of this tracing app? And what does its future look like?

The main aspect on how such an app will be effective is the number of downloads. To be effective, the tracing app has to be downloaded by 60% of the citizens of a country, as mentioned earlier in this article. Within a short period after implementing the app in all the mentioned countries, the downloads looked very promising. However, after a longer period the number of downloads disappointed. Considering the fact that in the countries where an app has been implemented the number of downloads never reached this percentage, the app cannot fulfil its expected maximum effectivity. As we can see in, for instance, Singapore, but especially in Australia, this has been the case. In both countries, the number of downloads were, and still are far below the required number to be effective. Hence, based on the current downloads, we can state it is not effective for a country to implement a contact-tracing app.

A major drawback for the number of downloads is that in all discussed countries, the app is made voluntarily to download. Put that together with the negativity that has been spread in the media about this app and it results in the number of downloads those apps have now. When the working of the app was not yet clear, media speculated about how the app could work. This resulted in citizens creating an opinion about the app without even knowing what it does and how it works. People had the fear that the app would be part of 'big brother is watching you'. Even though it is not proven true, but we think the lack of communication about the app in Australia resulted in fewer downloads than would have been with clear communication, because it is voluntarily. We do not state, however, that the app should have been obligated to download. For the effectivity that would have been the best case, since the number of people who must download it would definitely be reached. But in a modern western democratic society where people have free will, we believe that an app should not be made obligated to download.

Even though we state that based on current results implementing a contact-tracing app is not effective, we believe it can change. As mentioned, the app has had problems communicating between different smartphone models. It has been developed in a short period of time, so these development problems are not unexpected. Other development problems also occurred, which then were mentioned in the media and the same story happens as mentioned in the previous paragraph. However, the API from Google and Apple looks promising. At the time of writing the first apps using this API were implemented, for example in Austria. Together with a good campaign that removes any wrong ideas and thought about the app, we believe it still has a great chance to be downloaded many times and therefore can be effective.

DISCUSSION

In this article, the effectiveness of contact-tracing apps in the context of the COVID-19 pandemic has been researched. This article contributes to the understanding of the extensive literature that is available about the effectiveness of contact-tracing apps in the context of the COVID-19 pandemic. Furthermore, it provides recommendations on how to design a contact-tracing app for the COVID-19 pandemic with optimal effectiveness. This article is of importance, as a mobile contact-tracing app is said to be needed by [34] to support health services to control the COVID-19 transmission, to target interventions, and to keep people safe. Currently, a small amount of research exists about the effectiveness of contact-tracing apps and no overview is yet presented about important literature that does exist about this topic. The gathered knowledge and critical look upon aspects of a contact-tracing app have supported a recommendation for which aspects of the application to include in order to make the contact-tracing app as efficient as possible. This article critiqued simulation models and state-of-the-art applications, however, it does not take a stance on if the application, in the context of the COVID-19 pandemic, will be helpful. The study solely provides the building blocks for designing a contact-tracing application with the highest effectiveness.

App developers

The article contains an extensive literature review which provides the reader with a good and comprehensive overview of the existing literature relating the effectivity of contact-tracing apps. The recommendations in this article are based on the extensive literature review and are solely based on the effectivity of the contact-tracing apps. The recommendations are thus only provided on how to achieve the maximum achievable effectiveness of the contact-tracing apps. Other values are discarder, such as privacy. The recommendations are of particular value to app developers. It provides them with a bigger understanding of optimal effectiveness for digital contact-tracing apps and helps them designing a functional digital app in order to combat the COVID-19 pandemic. The app developers can specifically include the findings and recommendations of this study in a complete design that does take all other aspects into account such as privacy.

Miscellaneous values

The article solely focuses on the effectiveness of contact-tracing applications in the context of the COVID-19 pandemic. By discarding any other values, the opportunity emerges where one aspect is explored in great detail. Many aspects, like privacy, reliability and ethics, have great overlap within the field of our study. Our recommendations, for example, might therefore not always align with the privacy standards. We challenge the app developers to take the provided building blocks which this study provides and design with them, keeping other values, like privacy, in mind.

Human behaviour

Regarding human behaviour, it is the question whether users are going to download the contact-tracing apps when the effectivity is optimal. In the simulation models, it is possible to determine how many people have downloaded the contact-tracing app by changing a value. In the ASSOCC model, for example, the developers researched the effect of implementing the contact-tracing app into society by changing the percentage of people who downloaded it (60%, 80%, 100% users). This model is based on a set of artificial individuals which each have a set of given needs, attitude towards regulations and risks, and demographic characters [12]. Each artificial individual decides at each time what they should be doing, and the decisions are based on the individual's profile, state and social, psychological and physical needs [12]. So, the individuals in this model are also able to determine whether they want to download the app or not. However, when researching the effect of implementing a contact-tracing app, the developers assumed a perfect app aligned with all functional, legal and ethical requirements. In our study, legal and ethical requirements are however not taken into account, which means that it remains difficult to determine whether the users are going to download the app. It is therefore also not sure how users are going to deal with the contact-tracing apps and whether they deal with it as hoped.

Critical tracing efficiency

The calculated CTE values at 2.0% and 3.9% seem to be low. In conclusion, even if p will increase and R0 decreases significantly, it still results in a CTE that will indicate that a contact-tracing app in the Netherlands is not effective. However, past research [2] indicates higher values of R0 by a large margin, with or without little social distancing measures in place. So this does not indicate in any way that a contact tracing app could not have added value in the future.

Limitations

Several limitations occur according to providing the building blocks for a contact-tracing app with the highest possible effectiveness. Some aspects which have been discussed need more research in order to be validated and there are some limitations to the methods used in this study.

The use of sound or sonar in combination with BLE could possibly be a way to avoid false-positive results during contact-tracing. However, the combination has scarcely been researched and therefore it cannot be stated if this method is applicable. In order to conclude this, further research needs to be conducted first.

As the focus of the study lies with the effectiveness of the application, more research needs to be done on how to reach the adaption rate of at least 60%. The interface of the app could lead to reaching this percentage, or perhaps the government will obligate the society to download the application. This should be explored in more detail and would suit a follow-up study.

Critique has been given on simulation models and state-of-the-art applications. In the Netherlands, seven applications have been proposed for possibly becoming the contact-tracing app in the Netherlands. However, none of them seemed to reach the required standard. In order to support choices and critique within the study, interviews have been conducted with two of the seven app developers of these applications. Because only two out of the seven app-developers got interviewed, we might lack some critical information on the other applications. Insights in the values of the other applications could have led to a clearer understanding of important values to app-developers and their design methods.

In addition, the study discusses and critiques two simulation models. There are more models on contact-tracing which have not been discussed. If more simulation models would have been explored and compared there could have been more elaborate and new insights. ASSOCC and ABM have been selected to explore because of the easier access to ASSOCC and because of contact with an expert of the ABM model.

Throughout writing this article, the topic constantly changes, and new technology is being proposed. This makes it that this article only includes the possible information up and until a certain point in time. During and after the release of the article there could be new and improved methods and/or technology present which could make an app even more effective.

CONCLUSIONS

In this paper, several technologies and techniques regarding COVID-19 Apps have been examined. Several proposals regarding these implementations have been made.

Regarding contact tracing, calculations of R(t) and the CTE show that there is no need for a contact tracing application. However, since the measures are slowly being retracted, there is good reason to assume that the development of such an app has good value in the future. Researching applicability of data and collaboration with the RIVM for developing a corona app for the Netherlands is advisable. Furthermore, we suggest the use of second-order tracing, such that a high percentage of the population who would be affected and contacted in case of possible infection [24].

Looking at types of technology and approach of this App, our suggestions would be to use Bluetooth Low Energy (BLE), with the possible combination of sonar and/or sound use, such that the BLE detects the phones at a continuous pace, and the sound application could act as a safety switch to check whether there is an object such as a wall in between both phones to create a more reliable solution. As for the approach, we suggest a decentralized approach, because it would fit well regarding data issues and it will be more compatible with a Bluetooth based system. It is also used in the simulation models analysed.

Regarding our proposals for simulations, we suggest the use of behavioral models, which show a better performance in a crisis situation regarding the time between becoming infected and showing symptoms. Another thing that should be included is migration. Since the COVID-19 pandemic has an effect on travelling. Furthermore, the differences between the age of individuals, their living situation, background, and behavioral motives should be considered. This can help to identify the possible differences across individuals and how the contact-tracing apps can be expected to be used. Thus, resulting in a more reliable model.

Lastly, we found a lack of inclusion in the healthcare sector, which is quite important in a pandemic. We propose to include not only hospitals and the ICU into the models, but also psychiatric hospitals and nursing homes, since they have an increased risk regarding the spread of the virus. Implementation of these, can result in better accuracy of the simulation models. Keeping all these suggestions in mind, the effectiveness of a COVID-19 App should increase significantly.

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