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

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ABSTRACT

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 an mobile application in order to execute contact tracing more efficiently. The World Health Organization recommends a combination of measures: rapid diagnosis and immediate isolation of cases. However, there are likely many cases of undetected SARS-CoV-2 infection. Several mobile applications have been proposed to the Dutch government, yet one fits the expectations. In this article, we explore the effectiveness of such contact-tracing apps and explain how to reach the highest possible effectiveness such applications.

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. Many governments have since the outbreak 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 national economy. In the long term, this approach is not sustainable. However, leading to the need to find ways to reduce restriction on social interaction in all aspects of society without losing grip of 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 the Coronavirus, 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 brings a lot of difficulties with it, regarding the violation of the Dutch privacy legislation. In [10] is explained that we need a mobile contact-tracing app to urgently support health services to control the COVID-19 transmission, target interventions and keep people safe.

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

In this article we present our insights on the effectiveness of digital contact-tracing applications in context of the COVID-19 pandemic. These insights lead to several recommendations on how to reach the highest possible effectiveness when discarding influenceable factors like privacy. The state-of-the-art applications' values will be reviewed together with the developers' views on their product. Simulation models will be analysed in order 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 will present a well-structured argument.

We expect the findings of the article to bring us a well-structured list on how to achieve the highest effectiveness of a digital contact-tracing application in 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.

METHODOLOGY

A various number of actions and steps were taken in this research. The study is a literature review. The main sources of information can therefore be found in the related work section. In the Related Works section of this study, other research towards particular aspects of a contact-tracing app have 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 could support and critique the previous explored studies and research. Based on the gathered and analysed information, our view upon several aspects will be 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 findings need to be compared with already existing knowledge. We have gained knowledge on the following topics: effectiveness of contact-tracing; application of technology; simulation models and state-of-the-art mobile apps. This knowledge will help us focus on the critical aspects of the applications' effectiveness and create a well-structured view on 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 will be launched should work properly to begin with. The app will therefore need to reach certain benchmarks.

One of these benchmarks is the app adoption rate [8] 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 [11]. According to [12], if 70% of the population uses smartphones (assuming that there is no app use there for children aged under 10 and the fact that people aged over 70 have a low smartphone use), and epidemic like COVID-19 can be suppressed with 80% off all smartphone users using the digital contact-tracing app, which is equal to 56% of the total population. Contact-tracing using smartphones can be beneficial even with a partial adoption among the population [12]. In order to contain the spread, the adoption rate should at least be higher than 60% [8]. The developers of DCTS [9] think this percentage must be even higher, the DCTS (Digital Contact Tracing System) needs a broad acceptance among the population, which would be more than 70% in order to have an impact.

Whenever an person has been in contact with an infected individual, the application will send a message to the possible infected individual about the situation [9]. This message should bring insights to the user and provide it of clear advice and instructions. In order 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 [9]. 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 [13]) needs to be taken into account. According to [14], whenever the detection time of an infected person is fixed, a too large 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. Effectiveness may therefore be very sensitive to the latent period, especially with little variation [14]. The sensitivity may be large in the case of single-step tracing [10, 15, 16]. This could be solved in means by introducing a variable detection time [14]. The DCTS [9] proposes to apply second order tracing. The DCTS is being evaluated together with intervention strategies, and these results are being crosschecked using both deterministic and Monte Carlo based approach models [17]. Based on these models, applying only first order contact tracing might not be enough. Therefore, [9] wants to enable both first and second order tracing. "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" [9].

Because the digital contact tracing applications are often installed on the user's mobile phone, there occur several limitations [8]. 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 in order to realise this, which will be discussed. Which approach is best applicable for the highest effectiveness and what are the 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 [20], GPS [8, 9, 20, 21, 22], cellular network geolocating [23, 24] and using mobile network data [9]. Due to the fact that it is supposed to work indoors as properly as outdoors, these solutions are not reliable [9]. Many believe that Bluetooth tracing is the most suitable and has also been demonstrated effective for proximity detection [4, 18]. Because Bluetooth has an effective range of round 25 metres, the use of signal strength can identify whenever another device is within the 2-metre rule according to social distancing measurements [4, 18, 25]. Therefore, many papers [1, 2, 3, 4, 5, 6, 7, 8, 9, 18, 19, 20, 51] propose the use of Bluetooth for proximity detection.

The use of Bluetooth can be split up in two main methods. Several papers propose the use of Bluetooth BR/EDR [1, 2, 3, 18] whereas others propose the use of Bluetooth Low Energy (BLE) [4, 5, 6, 7, 8, 9, 19, 51]. 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 [9]. The probability of the devices detecting each other successfully within 10 seconds is close to 100% [9]. In its essence, BLE is designed for continuously scanning the background [8],

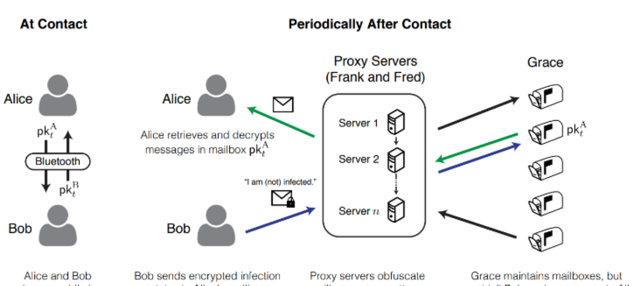


Figure 1: Overview of contact tracing based on private messaging systems. When Alice and Bob are near each other they exchange public keys as tokens. They then periodically encrypt (using each other's public key, followed by the public keys of the proxy servers) a message indicating their infection status, 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 [1].

TraceTogether [1] is the best 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 send to the person who he or she has been in contact with. The individuals who receive a message are able to decrypt the message by using the key they receive earlier and are able to view the infection status of the other anonymous individual. In this case, the proxy server is added in order for preserve the privacy of the infected individuals from the government (see Fig. 1).

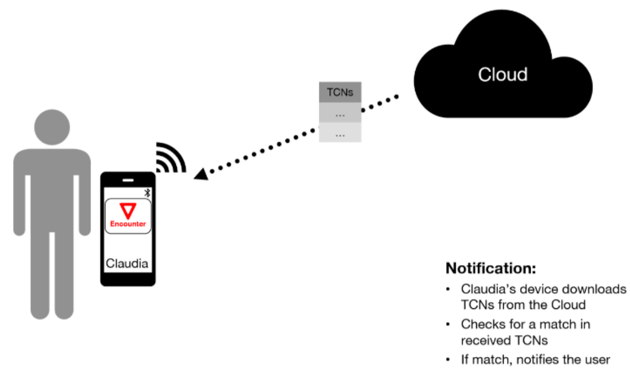


Figure 2: Overview of checking encounters. Every device can check its recorded TCNs against the reported TCNs on the server. If a device finds a match, it notifies the user [9].

In [9], the authors propose the Digital Contact Tracing Service (DCTS). The DCTS is based on the phones emitting and scanning for Bluetooth signals, and thereby exchanging so called Temporary Contact Tokens (TCNs) [9]. The approach uses BLE, mainly because of its continuous scanning in the background. The DCTS will activate BLE and generates 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 [9]. When a device spots another device's advertised TCN, it will be stored and phones will exchange their tokens. Whenever an user is confirmed infected, he or she is able to 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 your 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). In order for the DCTS to allow second order tracing [9], the user who gets notified because they have been in contact with an infected individual also uploads their TCNs on the server.

The DCTS makes use of a decentralised approach [9], 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, the personal data is controlled by the government authority [28]. There is a strong growing trend globally, and especially in Europe, which shows that the decentralised approach would be preferable [27, 28].

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 [8]. 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 [8], which limits the continuous transmission of beacons. Also when sitting on the couch while using a mobile device, the signal may reach through the walls at which the couch is located, whenever another device is in reach of the Bluetooth signal on the other side of the wall, it will identify the situation as if the individuals carrying the devices have been in close contact with each other. However, this is not correct.

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 [32]. Simulation models can be useful to obtain more of an understanding about a current system by testing scenarios using specific software tools [32]. It can be seen as an incorporating time that reflects to any changes that occurs over time [32].

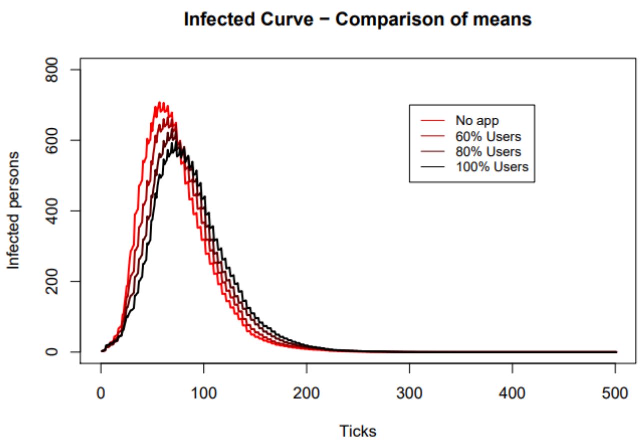
Because of the COVID-19 pandemic, the government has to come up with a set of policies to contain the virus. Multiple simulation models are used to see what effect certain policies have on society. The mobile contact-tracing app is one of these policies which can be tested with the simulation models.

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 [29]. 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) [29]. 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 [29]. ASSOCC is built in NetLogo (see Fig. 3), which is a multi-agent programmable modelling environment [33]. 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 [29]. Each artificial individuals decides at each time what they should be doing. These decisions are based on the individual's profile, state and social, psychological and physical needs [29]. 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 [29]. 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 [29].

Figure 3: ASSOCC user interface. The user interface depicting houses, workplaces, hospitals, schools, station, and people's movements [29].

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 [30]. The effectiveness of such an app was researched by performing three experiments. First, the effect of the app depending on different percentages of 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 increasement of app users results in a sharp



increasement of needed testing (see Fig. 5) [30].

Figure 4: Infected Curve – Comparison of means (01). Impact of app use on number of infected agents. [30].

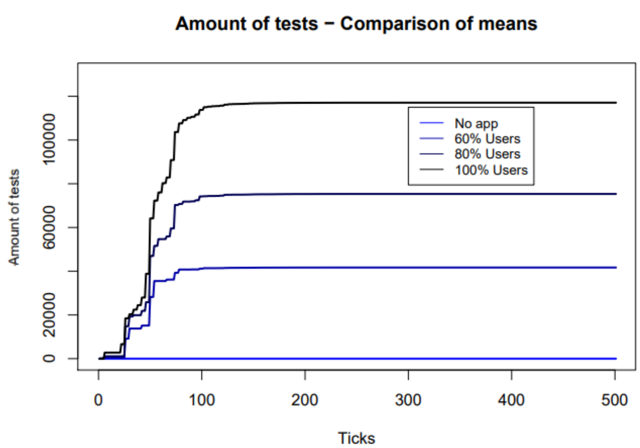


Figure 5: Amount of tests – Comparison of means (01). Amount of agents to be tested under different app use configurations [30].

Next, the effect of using the app was compared with random studied 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) [30].

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) [30].

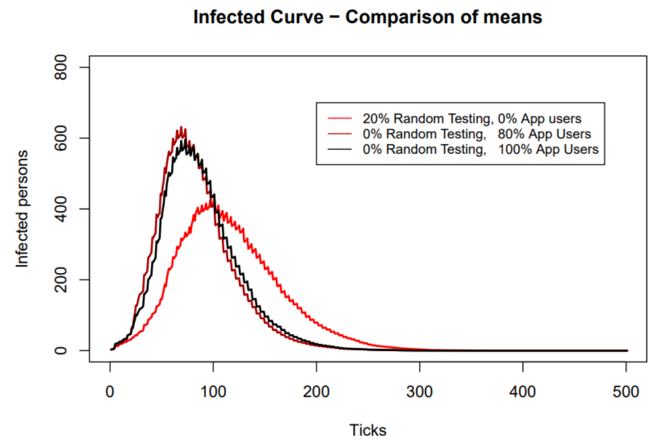


Figure 6: Infected Curve – Comparison of means (02). Comparing app use with random testing [30].

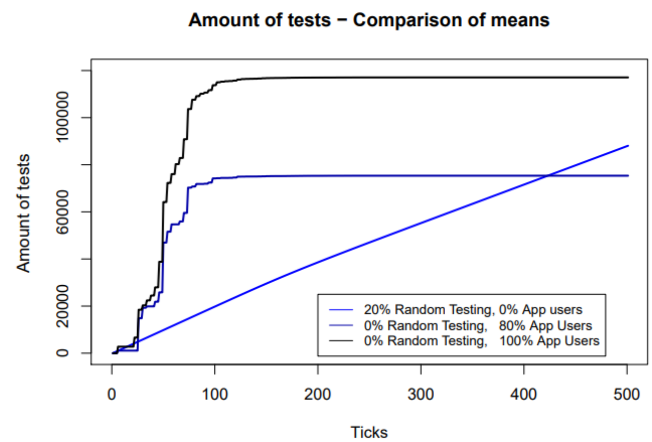


Figure 7: Amount of tests – Comparison of means (02). Amount of tests under different conditions. [30].

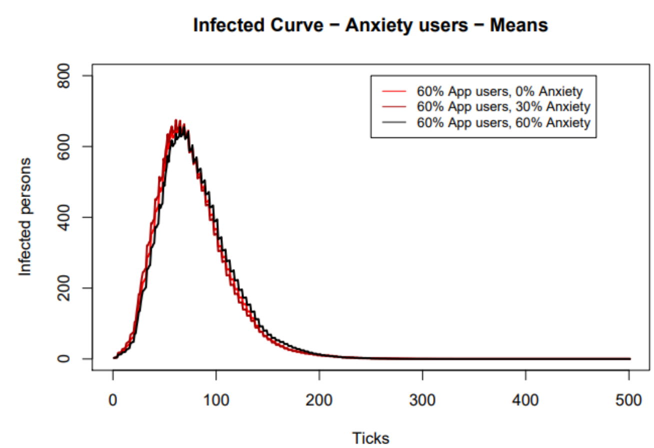


Figure 8: Infected Curve – Anxiety users - Means. Influence of risk averse agents. [30].

It can be concluded from the model 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 [30].

The Dutch government based their decision of implementing a contact-tracing app on the COVID-19 agent-based model (ABM) with instantaneous contact tracing. It was developed to simulate the spread of COVID-19 in a city, and to analyse the effect of passive and active policies [34]. The demographics of this model are based upon UK national data for 2018 from the Office of National Statistics [34]. 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 [34].

The active policy of digital contact-tracing was studied in this model. When contact-tracing, a random number of interactions is assigned to the model. The usage of the app is just as 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 [34]. The ABM allows to explore this policy and its effects and contains the option for recursive tracing of contacts of contacts [34].

Both the ASSOCC model and the ABM are agent based simulations. This means they are able to handle with the uncertainty and variability of the system [29]. Both models are however constructed differently, which leads to different results of the effectiveness of a contact-tracing app. In this paper, these two models are 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. Several of the state-of-the-art have been explored in this paper. The following applications discussed are purely selected on relevant technologies, which are most likely to be effective. This mainly results in applications which make us of Bluetooth. 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 [43].

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 [1, 43]. It was released on March 20th by the city-state and was not made obligated to download. One-week later Singapore made it freely available for developers worldwide [44]. 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" [45]. 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 [44]. However, at this point, less than 25% of their citizens had downloaded the app [46]. 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 [47] looked at the technical details behind Singapore's app. Although the app has privacy concerns, TraceTogether is a very good example of not getting 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'" [47]. The individuals who did download the app experienced technical difficulties when using it [48]. 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 [48].

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. Their app is based on the source code of the TraceTogether [1] 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 the Australian citizens to download the app [49]. Health minister Greg Hunt stated the government's target for uptake of the app is 40% of the population in order to ease some restrictions in states and territories [50]. After four weeks no official numbers have been released but based on estimations of the number of Australians with smartphones, it is now about 1.5m under that target [50]. In four weeks' time 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 [50]. The applicable solution to this problem for both Singapore and Australia is probably to use the Apple-Google API [52, 53]. The Australian government is currently evaluating this, but according to a Melbourne cryptographer, Vanessa Teague, it would require a major overhaul to the app [50]. Recently, Apple and Google have been working together to fix the technical problems and made technology, the mentioned API, that is available for governments to use for their Corona tracing apps [53].

Not many European countries have succeeded in launching an 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) [24] and was released on March 25. Within a week it had been downloaded over 100.000 times [54]. 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 their Stopp Corona app [55].

The second corona 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 26th of May. 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 the DP3T technology [24, 56]. The app would need improvements according to critique, however, these necessary amendments cannot be implemented earlier than August [57].

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 [58]. 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 [59]. 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” [59].

3 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 [12] and [8] 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% [12]. In the Netherlands, 87% of the population (individuals above the age of 12) uses a smartphone in 2018 [42]. 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 order for the infected individuals to take action, a message should be send 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 [9]. 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 [8], 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, we suggest 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 [9], and thereby increase the effectiveness tremendously.

Technology application

For contact tracing, solutions such as Wi-Fi MAC address sniffing, GPS, and cellular network geolocating have hall been proposed. However, the most suitable for use in CTA is often believed to be Bluetooth tracing. Many point to the effectiveness for proximity detection, that has already been demonstrated [4, 18]. They also claim 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 [38].

However, the original Bluetooth BR/EDR protocol, while it was designed for primarily “pairing” phones with other devices such as computers, Bluetooth speakers, or keyboards for the purpose of data communication, it 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 [8]. The energy costs would be higher when using continuous transmission and listening.

In order to cope with the fact that several devices are able to use the Bluetooth signal, Bluetooth scheduling will need to take place [8].

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 [37], 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 that we propose, 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 safe switch to check whether there is an object such as a wall in between both phones. SONAR-X [39] claims to be more accurate than BLE due to less false-positives. Their technology could be combined with the reliability of BLE and lead to an even more reliable solution.

For an 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 the personal data. With a decentralized approach, the collected data will be stored locally with the user [28]. 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 the government authority. Centralized apps follow mainly the PEPP-PT (Pan-European Privacy-Preserving Proximity Tracing) [23, 39], 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) [24, 40], but this is only partly decentralized. No pooled data is collected, which largely mitigates the privacy risk. The none-infected individuals' data are decentralised based, and the infected individuals' information will be collected anonymously to a central database [28]. Google and Apple will release an exclusive decentralized framework which will be more compatible with IOS and Android systems [41].

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 level 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 [28]. 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 [27], 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 [27, 28].

Simulation model comparison

The ASSOCC model and the ABM differ from each other Simulation model comparison

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 [62], the contact-tracing apps are not effective considering the containment of the virus. According to the ABM [34] 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 [31]. 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 [31].

The major differences between the ASSOCC model and the ABM are related to a number of specific properties of the COVID-19 virus.

The first property lies in the time between becoming infected and showing symptoms [31]. This time is quite long. In the ABM this time is called Tsym. It is drawn from gamma distributed variables of the time taken to make the transition [34]. 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 [31]. However, these mathematical models do relatively well in 'normal' situations, but in crisis situations, people behave differently and do not behave according to expectations [31]. 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 where in 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 [31]. The AMB currently does not have data on the distribution of the duration of interactions. The effect of this on 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 [29]. 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 [31]. 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 [31]. 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) [34]. 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 [34]. The values match the OpenABM-Covid-19 baseline parameters [34]. 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 elderly (70+ years). The value of interactions in a household also match the OpenABM-Covid19 baseline parameters. The values are acquired from empirical estimates [34]. 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 [34]. 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 [34]. 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 [34]. 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 [34]. 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 [34]. 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 [34]. 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 [34]. 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" [62]. 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 [62]. 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 [62]. This personality includes whether individuals are for example risk-avoidant and keep their social distance even when the chance of getting infected is low [62]. Therefore, as decision between the following implementation has been made: "the preparedness for obeying the rules and when not obeying, actively looking for crowds" [62]. Furthermore, individuals at different ages have a different chance of infecting others in the ASSOCC model. The elderly are effected very heavily in this model. To conclude, in the ASSOCC model, statistical data is used to initialize the age of the individuals and the household settings [62].

The third property contains the demographics and living arrangements [31]. 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 in order to model the effects of traveling. 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) [62]. 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 [34]. 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 stuff [34]. 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) [34]. 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 [29]. 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) [60]. 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" [62].

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 [34]. The models should contain more details about the transmission within hospitals and patient flows.

Simulation model additions

One possible expansion on the simulation model(s) for the spread of covid-19 existing presently involves modelling nosocomial transmission, spread of the virus within medical institutions. Plans for modelling possible nosocomial transmissions through various staff-patient interactions have already been made seen the large impact of the outbreak on medical facilities and the dependence of infection development on good healthcare [34].

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 [62]. These categorizations narrowly match those utilized in the Dutch healthcare system [71], 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. Furthermore 26% of patients required admission to the ICU [70]. Another retrospective study showed how a sample of 1716 health workers were infected together formed 3.84% of 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" [68]. However, as seen in the SARS out-break, 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 [62], 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 [63].

For 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 good hand and environmental hygiene [63, 69].

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), high-flow nasal cannula (HFNC) and patient transportation [68]. Even though reports suggest that NIV and HFNC were for used somewhere between one third and two thirds of covid-19 patients admitted to the ICU and that there is a suspected connection between aerosol generation by these devices and transmission of the virus, as of yet minimal data exists to definitively prove this connection [69]. Even still, some epidemiological statistics show that NIV was in some form associated with 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) [69]. 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 [69].

As of right now, insight 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 [72] 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 medium for transmission of the virus. Recent studies show that mental health care is much needed due to the level of pressure put on medical staff, particularly ones working at the ICU [65]. 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 [64] and nursing homes [72] are prone to facilitating spread of the virus. Modelling these facilities within society using the latest statistics on 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.

State-of-the-art applications

Recommendations

DISCUSSION and CONCLUSION

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