Estimating the Eeffect of COVID-19 Contact Tracing Application Using Agent-Based Simulation

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Abstract—**In this paper, we estimate the effectiveness of COVID-19 contact tracing applications using agent-based simulations. We develop a simulation model and see how many infected patients can be reduced using the applications. In order to investigate the effectiveness of the applications, we enlarge the tracing area from direct contacts to indirect contacts. The results of our agent-based simulation show that detecting indirect contacts can reduce the number of infected patients.**

Keywords—COVID-19 contact confirming application, agent-based simulation, direct and indirect infection

I. Introduction

Since 2020, contact tracing applications are introduced in several countries to cope with COVID-19 epidemic. However, they face challenges to increase the number of users who download the applications and activate them for contact tracing. Hinch et al. [1] released a report which states, "we find that the epidemic can be suppressed with 80% of all smartphone users using the app, or 56% of the population overall." This is comparable to the rate of WhatsApp or Facebook Messengers in some European countries [2]. This statement is misunderstood in Japan such that "contact tracing applications should be used by more than 80% smartphone users, otherwise it is not effective." The results of our agent-based simulation show that contact tracing application is effective even if the rate of persons who use the contact tracing application among the population is low.

Hinch et al. continues their work to investigate the effect of exposure notifications. Consequently, they release a paper of Abueg et al. [3]. In their work, they employ the same simulation model in Hinch et al. [1]. They develop a simulation model using the synthetic populations in Washington state, USA. They wrote "we found that exposure notification can meaningfully reduce infections, deaths, and hospitalizations in these Washington state counties at all levels of app uptake, even if a small fraction of the population participates."

In this paper, we investigate the effectiveness of a contact tracing applications using the simulation model developed by Kurahashi [4]. He compared preventing measures for COVID-19 using his simulation model. He developed two artificial cities and conducted several preventing measures to compare each measure with a basic case where no preventing measure is conducted in the cities. We employ his simulation model to investigate the effectiveness of a contact tracing application using the direct and indirect contact information.

II. COVID-19 Infection Model

A. Infection Model Using Agent-based Simulations

We employ the agent-based simulation model proposed by Kurahashi [4]. We increase the population ten times larger than the original model. There are two cities in the model. Each city has 1,000 families with a husband, a wife, and their two children. The city also has 800 families of an aged couple of a husband and a wife. Therefore, each city has 5,600 populations in total. There are 11,200 persons in the whole model. All persons have social activities in the cities. They will go to their offices, schools or shopping malls. All adults in the 1,000 four-member families go to their offices for their job. All of their children go to their schools. There is one hospital in the model and 50 workers come from each city. Half of workers commute to their office by trains. Aged persons do not work but go to the shopping mall under a specified probability. Adults also visit the shopping mall under a specified probability.

In offices, schools and trains, each person has their own fixed seats. That is, they always have the same position in their offices, schools or trains. On the other hand, they have random positions in the shopping mall. They visit the shopping mall probabilistically. We assume that the shopping mall always has capacity visitors. That is, no room is available in the shopping mall. Some visitors come from other cities to the shopping mall. We define the same rate of infected persons in those cities.

We employ the following infection process. When a person has another person as a neighbor in their offices, schools, trains or shopping malls, an infection can be occurred probabilistically. We assume that there is one opportunity of a probabilistic infection in each hour. One time in the morning in a family, One time in a train, eight times in offices, six times in schools, three times in a shopping mall, one time in a train, and one time in the night in a family.

We define the infection process according to the analysis of the infection [5,6]. Fig. 1 shows our process. The virus has an incubation period of five days after a patient is exposed. Three days after the patient is exposed, the virus begins to infect others. Symptoms such as fever, cough and so on appear six days after the patient is exposed. After getting fever, 90% of patients go to a clinic or a hospital. 50% of the patients have a PCR test to detect the virus after consulting a doctor. The patients who test positive by PCR test will be hospitalized. On the other hand, the patients who test negative will have other medication. Those who do not have PCR tests, they will be quarantined to observe their condition. 20% of the infected patients become serious 20 days after they are exposed. All

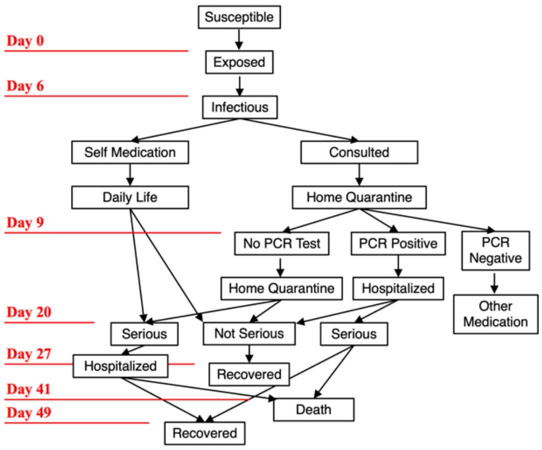


Fig. 1. Infection Process.

serious patients including those who have not consulted should be hospitalized. By 41st days, 0.06% youth, 0.21 adults, and 1.79% aged patients will die. It should be noted that if patients have appropriate medications, they can recover from their serious situations. At that time, we can reduce the rate of death. Patients who are not serious will be recovered probabilistically by the 27th day. Serious patients who can avoid deaths will be recovered probabilistically by the 49th day. Those who are recovered are not susceptive to the virus.

When s/he does not go to the hospital after s/he get a fever at the 6th day, s/he tries to have a self-medication. S/he takes a medicine bought at the drugstore. S/he continues to have her/his own daily life. Therefore, s/he will spread viruses if s/he is infected. S/he is recovered or becoming serious by the 20th day. If s/he becomes serious, s/he will be hospitalized.

We define the probability of the infection by the virus according to the basic reproduction number released by World Health Organization (WHO). We denote the days of infected by d, and the number of persons whom an infected patient contacts closely in a day by h, the probability of infection r can be written as follows:

$$r = R_0/(d \times h). \quad (1)$$

We define the probability of being recovered, and that of death as follows. We define the maximum number of days after having a fever by max_n. The probability of being recovered at the n-th day by n / max_n. We set the value of max_n for those who are not serious as 21, and for those who are serious as 43. Cases of deaths are happened only from serious patients. We define the probability of death at t-th day after being serious by t / max_t. The value of max_t is the maximum days after being serious, and we set it as 21.

Patients in the hospital have medications and they have the probability to avoid being serious. We denote the number of days after being exposed by j. The probability to avoid being serious or death by $1/j$. Since the earliest hospitalization is Day 10 after having a PCR test, the probability becomes 1/10 or smaller. Patients who avoid being serious, they will become patients who will recover. Patients who avoid death, they will be patients who are serious and be able to recover.

B. *Contact Tracing Application*

We implement a contact tracing application according to specifications of Japanese Government. The application released in Japan is called COCOA (COntact COnfirming Application). It employs Google-Apple contact tracing API. The smartphone that installed and activated the application can record smartphones that are also activate the application when they are within a specified distance for a specified duration. When someone who has the application reports s/he becomes positive in a PCR test, s/he should get a processing ID issued by public health centers. Using the issued processing ID, s/he can report s/he is positive. The smartphones that activate the tracing application will receive the coded IDs of the positive patients (each coded ID has no identification information about the patient). If the smartphone of recipients of coded IDs records the history of contacts that are generated by the coded IDs, the recipients will understand that s/he had contacts with a patient who becomes positive. The application records a history of contacts for 14 days. The government of Japan modified the length of history from 14 days to two days at the modification on December 15, 2020. We specified 14 days in this paper.

Patients becomes positive at the following cases:

1) When patients who have a fever more than 4 days and get a PCR test. Then s/he becomes positive.

2) When patients become serious, then being hospitalized.

3) When smartphone users receive a contact information and get a PCR test. Then s/he becomes positive.

In the real operation, not all patients who are declared positive register themselves as positive, we consider all patients register their situation when they installed and activate the application. We employ these specifications of a contact tracing application in this paper. TABLE I shows the difference between Oxford model by Hinch et al. [1] and the proposed model in this paper. The main difference between Oxford model and this paper is that patients register the application before being consulted by a doctor in Oxford model, but the patients register after being declared as positive by PCR tests in this paper. Oxford model encourages recipients of contact notifications quarantine themselves before being declared as positive by PCR tests.

Keep these differences in mind, Hinch et al. [1] show that more than 80% smartphone users should install the application in order to suppress the number of infected patients as it was before the lockdown in England.

III. SIMULATION RESULTS

In our simulations, there is one infected person randomly specified at the beginning of simulations. TABLE II shows the parameter specifications employed in this paper. The basic reproduction number is randomly given to each infected patient between 1.4 to 2.5.

We show the simulation results when we vary the value of possession rate of contact tracing applications. We conducted 100 trials using different random numbers. Among 100 trials, we found that there happen no spreads of viruses in some trials. Therefore, we show the average, median, maximum and minimum number for the number of days to no infected patients, the number of infected patients, the number of serious patients, and the number of deaths over the trials in which the number of positive patients becomes larger such as pandemic in TABLE III. In the cases of no pandemic where the increase of the patients is not observed, an initial patient may select self-medication and quarantine her/himself by s/he gets better without seriousness. The number of days to end means that it is the day when there are no infected patients in the modeled two cities.

TABLE I. The Difference Between Oxford Model and the Proposed Model.

	Oxford Model	Proposed Model
Model	Individual-based network	Cell model
Types of networks or cells	Household, office, circle, transportation, event	Household, office, school, transportation, shopping mall
The number of contacts	Number of contacts based on ages Double probability in household when quarantining	Household 2times, office 8, school 6, transportation 2, shopping mall 3
The number of days until fever	6 days	6 days
Hospital infection	N/A	N/A
Basic Reproduction	3～3.4	1.4～2.5
Registration	Including registration besides COVID-19	50% of patients with fever go to hospitals

	Oxford Model	Proposed Model
Start of quarantine	Self-declaration and receipt of contact notification	PCR positive
Target of quarantine	Self-declaration and positive patients: 7 days Family of positive: 14 days Contacts: 14 days	Positive: until cured Family of positive: Not required Contacts: PCR test
Submission to self-quarantine	2% of contacts will leave self-quarantine by each day	50% of patients with fever has daily life 50% of patients with fever keep quarantining
Possession of smartphones	The rate by age	The rate against to whole population
Possession of the application	The rate against to whole population	The rate against to whole population
Record accuracy	80% (No record for 20%)	100%
Contact	1st and 2nd degree	1st and 2nd degree

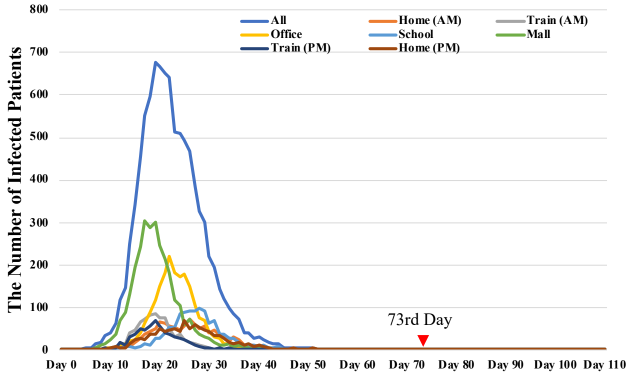
TABLE II. Parameter Specifications

Parameters	Objects	Values
Infection Probability	Young / Adult	0.008 – 0.012
	Aged	0.035 – 0.064
Probability to Become Serious Patients	Young	0.0090
	Adult	0.0300
	Aged	0.2800
Death Probability	Young	0.0006
	Adult	0.0021
	Aged	0.1790
Probability to Recover at *n*-th Day from Being Exposed	Not Serious Patients	*n* / 21
	Serious Patients	*n* / 43
Probability to Die at *t*-th Day from Being Serious	Serious Patients	*t* / 21
Probability to Avoid Being Serious or Dying	All Patients at All Ages	1 / *j*
Probability to Go to Shopping Malls	Adult	0.28
	Aged	0.50
Rate of Infected Patients in the Shopping Mall		# of Patients / # of Survivors in the modeled cities

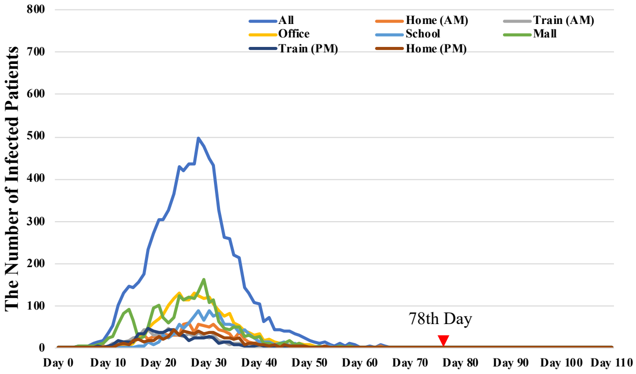
TABLE III. Simulation Results Using Contact Tracing Application (Notifications Are Sent to 1st Degree Contacts)

Rate of Activated Applications		**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Number of Trials Pandemic Happens		96	82	86	89	82	83	89	84	88	89	93
# of Days to No Infected Patients	Average	75.6	74.3	76.0	78.7	80.0	81.5	83.8	86.1	89.0	93.9	94.6
	Mean	74.0	73.0	75.0	78.0	79.0	81.0	83.0	85.0	88.0	92.0	93.0
	Maximum	94.0	95.0	92.0	102.0	98.0	102.0	100.0	109.0	113.0	117.0	123.0
	Minimum	63.0	66.0	65.0	67.0	69.0	70.0	68.0	71.0	74.0	78.0	76.0
# of Infected Patients	Average	9297.4	9273.4	9212.5	9164.4	9093.8	9007.5	8920.5	8818.6	8707.7	8572.0	8440.0
	Mean	9292.5	9275.0	9219.5	9171.0	9084.5	9011.0	8921.0	8813.5	8712.0	8566.0	8439.0
	Maximum	9430.0	9413.0	9322.0	9279.0	9253.0	9149.0	9061.0	9010.0	8868.0	8727.0	8635.0
	Minimum	9189.0	9159.0	9086.0	9058.0	8961.0	8883.0	8747.0	8674.0	8496.0	8395.0	8212.0
# of Serious Patients	Average	1152.0	1141.9	1133.0	1128.6	1116.5	1106.5	1090.8	1077.6	1071.1	1057.7	1042.0
	Mean	1152.5	1143.0	1133.0	1126.0	1115.5	1102.0	1093.0	1076.0	1070.0	1060.0	1039.0
	Maximum	1214.0	1241.0	1209.0	1184.0	1177.0	1179.0	1141.0	1155.0	1164.0	1121.0	1113.0
	Minimum	1080.0	1086.0	1072.0	1046.0	1055.0	1040.0	1045.0	995.0	1003.0	1002.0	967.0
# of Deaths	Average	78.4	80.0	78.0	76.7	75.1	74.5	73.5	72.9	72.4	71.4	70.6

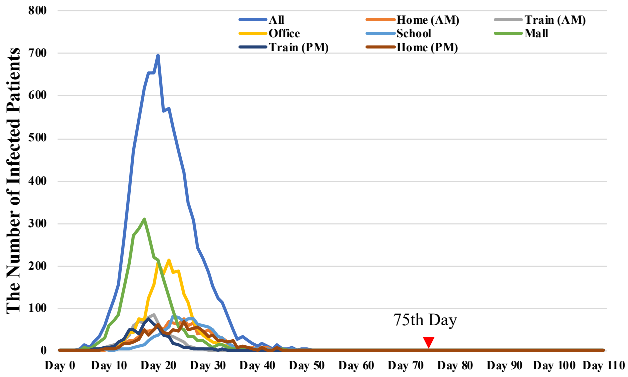
Mean	79.0	80.0	79.5	76.0	75.0	75.0	73.0	73.0	72.5	70.0	71.0
Maximum	94.0	100.0	95.0	94.0	102.0	93.0	94.0	90.0	86.0	91.0	92.0
Minimum	58.0	60.0	48.0	57.0	54.0	50.0	57.0	55.0	56.0	54.0	51.0



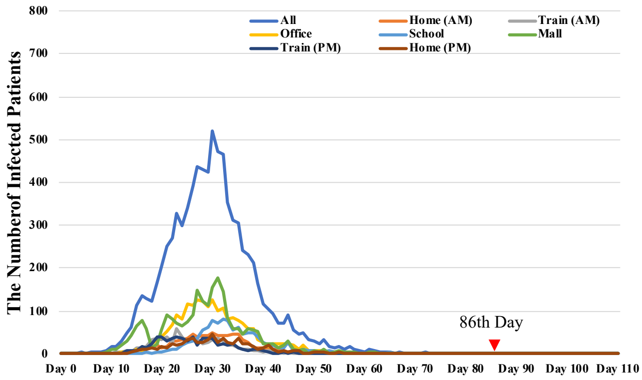
(a) Maximum Infected Patients: 0% Activated



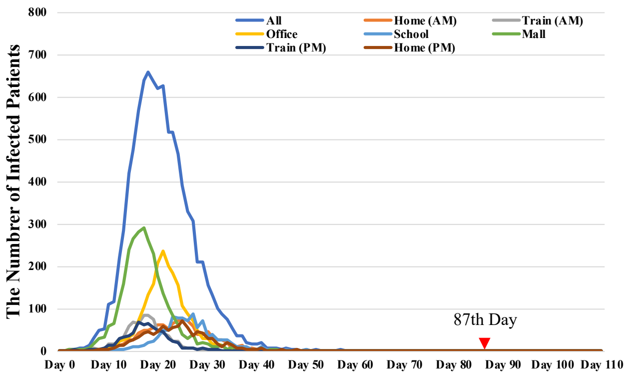
(b) Maximum Infected Patients: 100% Activated



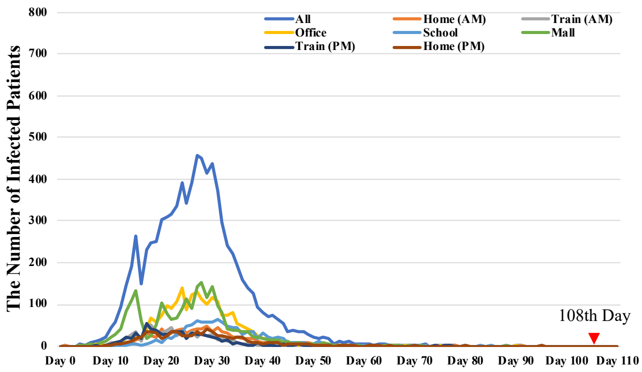
(c) Top 25% Infected Patients: 0% Activated



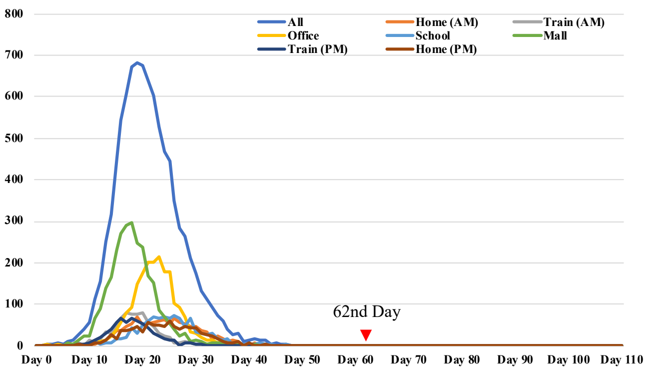
(d) Top 25% Infected Patients: 100% Activated

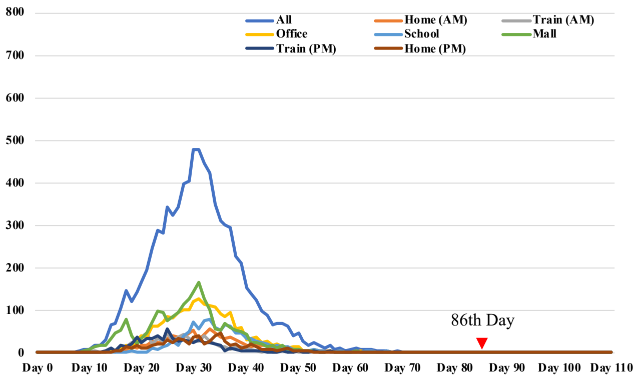


(e) Mean Infected Patients: 0% Activated



(f) Mean Infected Patients: 100% Activated





(g) Bottom 25% Infected Patients: 0% Activated

(h) Bottom 25% Infected Patients: 100% Activated

Fig. 2. The Number of Infected Patients by Places.

From TABLE III, we can see that the number of infected, serious and dead patients decrease as the rate of activated applications increases. When 100% of users activate the tracing application, the number of infected, serious and dead patients decrease 10.2%, 10.6%, and 11.0% against no users activate the application, respectively. Fig. 2 shows the number of infected patients by places where they are infected in the trials of maximum, top 25%, mean, and bottom 25% in the number of patients. From Fig. 3 (a), (c), (e) and (g), we can see that the number of infected patients in the shopping mall and offices are larger than those in other areas. When 100% persons activate the application, the number of infected patients in the shopping mall and offices are reduced. This reduces the number of patients in total. On the other hand, the number of days to no infected patients becomes longer in the cases of 100% active users.

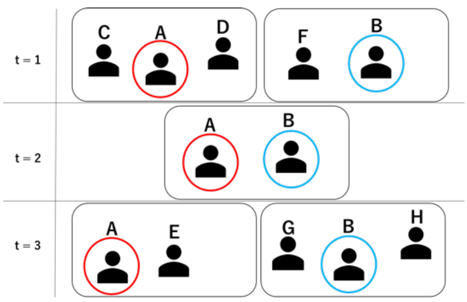


Fig. 3. 1st Degree Contacts and 2nd Degree Contacts.

TABLE IV. 1st Degree Contacts and 2nd Degree Contacts in Fig. 2.

Time	Contacts of A	Contacts of B
$t = 1$	C, D	F
$t = 2$	B	A
$t = 3$	E	G, H

	1st Degree	2nd Degree
A	B, C, D, E	F, G, H by B
	1st Degree	2nd Degree
B	A, F, G, H	C, D, E by A

In our simulation model, each person has a fixed seat in offices, schools and trains. Therefore, each person has contacts with fixed members in those areas. However, they have contacts with unexpected persons in the shopping mall. Therefore, the peak of the number of infections in Fig. 3 (a), (c), (e) and (g) is found in the shopping mall first. Then another peak is found in offices. After adults get infected at the shopping mall, they spread viruses at offices. From Fig. 3 we can see that the contact tracing applications can reduce the number of infections in the shopping mall. That results in reducing the number of infections in offices.

In TABLE III, it should be noted that the contact tracing application sends notifications only to 1st degree contacts. Fig. 3 and TABLE IV show our concept of 1st degree and 2nd degree contacts. When Person A is declared as an infected patient by a PCR test, then A registered her/himself in the contact tracing application. In our basic setting of sending notifications in TABLE III, only 1st degree contacts of A such as B, C, D, E receives notifications as shown in TABLE IV. When the applications employ 2nd degree contacts as the object of notifications, all persons in Fig. 3 receives the notification. From Fig. 3, we can see that Person F contacts Person B before Person B contacts Person A. If the source of the virus is Person A, there is no need to send a notification to Person F. However, it is needed if Person B has virus, but s/he does not have fever, s/he cannot recognize that s/he is spreading viruses. Therefore, we include Person F in the list of 2nd contacts.

We also conduct the case of notifications sent to 1st and 2nd degree contacts. TABLE V shows the simulation results in the form of TABLE III. We depict the average number of infected patients and deaths of TABLEs III and V in Fig. 4. The left axis shows the number of infected patients. The right axis shows the number of deaths. From Fig. 4, we can see that no difference in the number of infected patients can be found when the rate of application users is around 0% to 30%.

TABLE V. Simulation Results Using Contact Tracing Application (Notifications Are Sent to 1st and 2nd Degree Contacts)

Rate of Activated Applications		0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Number of Trials Pandemic Happens		90	88	86	87	85	84	90	90	84	85	90
# of Days to No Infected Patients	Average	75.2	75.2	80.0	82.3	84.9	91.0	99.1	108.0	117.2	142.4	176.9
	Mean	75.0	75.0	79.0	82.0	84.0	91.5	97.0	108.0	116.0	138.0	171.0
	Maximum	90.0	87.0	98.0	92.0	107.0	119.0	122.0	135.0	153.0	232.0	273.0
	Minimum	68.0	67.0	71.0	70.0	77.0	78.0	85.0	90.0	97.0	103.0	127.0
# of Infected Patients	Average	9286.1	9267.5	9184.6	9097.2	8955.2	8827.2	8655.0	8476.9	8301.6	8044.9	7849.4
	Mean	9285.0	9267.5	9188.0	9099.0	8945.0	8831.5	8652.0	8500.0	8299.0	8042.0	7842.0
	Maximum	9395.0	9375.0	9298.0	9203.0	9048.0	8957.0	8826.0	8623.0	8463.0	8309.0	8153.0
	Minimum	9154.0	9150.0	9000.0	8965.0	8848.0	8711.0	8517.0	8306.0	8175.0	7821.0	7546.0
# of Serious Patients	Average	1153.6	1149.9	1128.0	1120.8	1110.2	1090.5	1050.4	1035.4	1012.3	980.3	970.9
	Mean	1180.0	1172.0	1143.5	1136.0	1121.0	1114.0	1096.5	1066.0	1041.0	1022.0	1000.0
	Maximum	1227.0	1217.0	1206.0	1203.0	1187.0	1153.0	1161.0	1153.0	1097.0	1084.0	1085.0
	Minimum	1117.0	1102.0	1061.0	1056.0	1055.0	1045.0	1019.0	1017.0	954.0	917.0	903.0
# of Deaths	Average	79.3	77.8	77.0	76.0	76.0	72.7	71.0	71.2	69.5	67.0	65.6

Mean	79.0	79.5	81.5	77.0	76.0	71.5	74.5	72.0	69.0	67.0	65.0
Maximum	97.0	88.0	107.0	93.0	102.0	93.0	100.0	83.0	89.0	95.0	85.0
Minimum	60.0	63.0	67.0	59.0	62.0	57.0	56.0	54.0	58.0	46.0	51.0

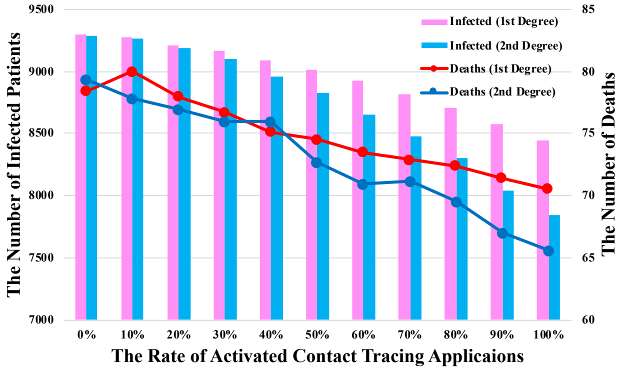


Fig. 4. The Average Number of Infected Patients and Deaths Using the application only with 1st Degree Contacts and with 1st and 2nd Degree Contacts.

Similar observation can be found in the number of deaths. From 0% to 50%, the number of deaths in the case of 2nd degree contacts is not less than the case of only 1st degree contacts. In the case of 40%, the average number of deaths in the case of 2nd degree contacts is larger. It is noted that we cannot conclude there is significant difference whether the application employ the 2nd contacts or not since the standard deviation of average number of deaths in the case of 100% use is 9.29. However, we can see the positive tendency when the application employs 2nd degree contacts when majority of smartphone users activate the contact tracing application.

IV. Conclusion

In this paper, we estimate the effectiveness of the contact tracing application to reduce the number of infected patients, serious patients and the deaths. As Abueg et al. [3] stated that they "found that exposure notification can meaningfully reduce infections, deaths, and hospitalizations in these Washington state counties at all levels of app uptake, even if a small fraction of the population participates," our simulation results also support the same conclusion. The contact tracing application can reduce the number of patients even if the number of application users are small among the population (see TABLE III and Fig. 4).

From the analysis of places where infections happen (see Fig. 2), we can see many infections happen in the shopping mall and offices. First infections may happen in the shopping mall, then next infections happen in the offices. By introducing the contact tracing application, the number of infections from contacts with unexpected persons in the shopping mall can be reduced.

We have examined the effect of using 1st and 2nd degree contacts to send notifications (see TABLE V and Fig. 4). Although we cannot see the significant results by introducing 2nd degree contacts, we can see the positive impact by using 2nd degree contacts to reduce the number of infected patients and deaths.

In this paper, we assume all the patients that are consulted as positive by a PCR test and register the application as a positive patient. We also assume all 1st and 2nd degree contacts will go to have PCR tests at next day after receiving the contact notification. However, Ranisch et al. [2] reported that 61% among notified contacts registered as positive patients when they conducted 349 simulated infections (that is, pseud infection) using the real contact tracing application in Spain (that is, Radar COVID app). From their report, we should expect a low registration rate as a positive patient in the real situation.

Ranisch et al. [2] pointed that the follow-up rate was only 10% in their experiment with simulated infections. The follow-up is made by those who receive notifications as a contact with a positive patient. They are expected to make a call to primary health care centers to reserve a PCR test in order to find whether they are a positive patient or not. They have not concluded that this is a real low rate since the participants in the experiment know that they receive the notifications of contacts as simulated infections. However, they study shows that we cannot expect 100% response from those who receive notifications from the application.

Acknowledgment

This work is partially supported by the Kansai University Fund for Supporting Outlay Research Centers, 2020, JST-Mirai Program Grant Number JPMJMI20B3.

References

[1] R. Hinch, W. Probert, A. Nurtay, M. Kendall, C. Wmant, M. Hall, K. Lythgoe, A. B. Cruz, L. Zhao, A. Stewart, L. Ferretti, M. Parker, D. Montero, J. Warren, N. K. Mather, A. Finlelstein, L. Abeler-Dormer, D. Bonsall, C. Fraser, Effective Configurations of a Digital Contact Tracing App: A report to NHSX, pp. 1-29 (April, 2020; August, 2020 updated).

[2] R. Ranisch, N. Nijsingh, A. Ballantyne, A. van Bergen, A. Buyx, O. Friedrich, T. Hendl, G. Marckmann, C. Munthe, V. Wild, Digital contact tracing and exposure notification: ethical guidance for trustforthy pandemic management, Ethics and Information Technology, pp. 1-10 (2020).

[3] M. Abueg, R. Hinch, N. Wu, L. Liu, W. Probert, A. Wu, P. Eastham, Y. Shafi, M. Rosencrantz, M. Dikovsky, Z. Cheng, A. Nurtay, L. Abeler-Dorner, D. Bonsall, M. V. McConnell, S. O'Banion, C. Fraser, Modeling the effect of exposure notification and non-pharmanceutical interventions on COVID-19 transmission in Washington state, npj Digital Medicine, vol. 4, no. 49, pp. 1-10 (2021).

[4] S. Kurahashi, Estimating effectiveness of preventing measures for COVID-19, a working paper on Prof. Kurahashi's website, pp. 1-7 (2020). http://www.u.tsukuba.ac.jp/~kurahashi.setsuya.gf/doc/wp-2020-n05.pdf

[5] The Novel Coronavirus Pneumonia Emergency Response Epidemiology Team, The epidemiological characteristics of an outbreak of 2019 Novel Coronavirus Diseases (COVID- 19) China, 2020 China CDC Weekly , vol. 41, no. 2, 145-151.doi: 10.3760/cma.j.issn. 0254-6450.2020.02.003 (2020).

[6] WHO-China, Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID19), https://www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf (2020).