Original Research

DIGITAL HEALTH

DIGITAL HEALTH
Volume 9: 1–9

DOI: 10.1177/20552076231178418
journals.sagepub.com/home/dhj
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Use of Bluetooth contact tracing technology to model COVID-19 quarantine policies in high-risk closed populations

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Abstract

Containment measures in high-risk closed settings, like migrant worker (MW) dormitories, are critical for mitigating emerging infectious disease outbreaks and protecting potentially vulnerable populations in outbreaks such as coronavirus disease 2019 (COVID-19). The direct impact of social distancing measures can be assessed through wearable contact tracing devices. Here, we developed an individual-based model using data collected through a Bluetooth wearable device that collected 33.6M and 52.8M contact events in two dormitories in Singapore, one apartment style and the other a barrack style, to assess the impact of measures to reduce the social contact of cases and their contacts. The simulation of highly detailed contact networks accounts for different infrastructural levels, including room, floor, block, and dormitory, and intensity in terms of being regular or transient. Via a branching process model, we then simulated outbreaks that matched the prevalence during the COVID-19 outbreak in the two dormitories and explored alternative scenarios for control. We found that strict isolation of all cases and quarantine of all contacts would lead to very low prevalence but that quarantining only regular contacts would lead to only marginally higher prevalence but substantially fewer total man-hours lost in quarantine. Reducing the density of contacts by 30% through the construction of additional dormitories was modelled to reduce the prevalence by 14 and 9% under smaller and larger outbreaks, respectively. Wearable contact tracing devices may be used not just for contact tracing efforts but also to inform alternative containment measures in high-risk closed settings.

Keywords

COVID-19, contact network, simulation study, branching process model, Bluetooth digital contact tracing tools, high-risk closed setting, migrant worker dormitory

Submission date: 5 September 2022; Acceptance date: 10 May 2023

Introduction

The coronavirus disease 2019 (COVID-19) pandemic has been the first in which digital contact tracing (DCT) tools have been widely deployed as part of several national responses, including in Australia,[1,2] China,[3,4] several states of the USA,[5,6] and multiple European countries including France,[7] Germany,[8] Ireland,[9] Italy,[10] the Netherlands,[11] Switzerland,[12] and the UK.[13] The ability to rapidly contact trace can assist in timely case identification, allowing for better case management and disease spread control by notifying individuals that they may be infected at an earlier stage.[14] The magnitude of outbreak peaks can also be reduced if, following such alerts, infected individuals modify their behaviour to reduce social interactions or to isolate themselves either before they become infectious or at an earlier stage of their infectious period. Early detection is especially important in closed or semi-closed populations—such as residential care homes, boarding schools, military

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camps, prisons, and dormitories—as the dense social network structure in such settings lends itself to explosive outbreaks, as has been witnessed both during COVID-19[15,16] and before.[17,18] Contact networks in such settings are characterised by a high degree of connectivity between individuals within the subpopulation and fewer connections beyond the subpopulation than members of the general population.

Singapore was the first country to roll out DCT tools with the launch of TraceTogether in March 2020, days after the World Health Organization declared COVID-19 to be a pandemic.[19] TraceTogether came in the form of a physical token and smartphone app, evolving through multiple versions to monitor access to key areas, proximity to others, and testing status of individuals. At the beginning of the pandemic however, an initial form of TraceTogether under the name of BluePass (BP), comprising a physical token only, was rapidly deployed to migrant workers (MWs) who work in heavy industries and construction, as they typically live in high-density dormitories. These dormitories observed large outbreaks during Singapore's lockdown in the early days of the pandemic—during which 56% of the residents had documented infections.[20,21] These BP devices were to be carried when inside and outside their dormitories,[22] were designed to be sufficiently durable to withstand use at worksites, and have a unique identifier that allowed for interaction events between devices to be tracked for the quarantining of close contacts of cases. After dormitory residents emerged from lockdowns in July and August 2020, they were subject to long-lasting restrictions on their movement, only being allowed to communicate with others that stayed in the same dormitory or worked in the same location to prevent further outbreaks.

In this study, we pursue two aims, taking advantage of the high volume of social interaction data recorded in an extraction of around 1000 residents of two dormitories working for the same company. The first was to quantify the nature of the contact network itself to gain insights into local heterogeneities that would possibly hinder control. The second was to use the empirical contact network to develop a realistic branching process model to explore the impact of policies that used varying stringency of quarantine to mitigate spread.

Methods and materials

Data collection in selected dormitories

Starting in October 2020, all MWs in Singapore were to carry BP devices for contact tracing purposes.[22] Each BP has a unique registration ID, and MWs are required to carry their own BP at all times to track interactions.[23,24] In February 2021, BP devices were updated[25] with improvements in design. As to the time to collect contact information, MWs were only allowed to communicate with others in the same dormitory or at workplaces, and all MWs assigned to the same dormitory should work for the same company. In collaboration with Keppel Corporation, we conducted fieldwork in two MW dormitories, Acacia Lodge (Dorm A) and Cassia@Penjuru (Dorm C), to obtain records of interactions from BP devices. We recruited 1611 MWs using convenience sampling, which is a non-probability sampling method to obtain samples from a group of people who are easy to contact or to reach, with approximately equal numbers in each dormitory, and after obtaining verbal informed consent, we extracted their records of interactions for the period of February to April 2021. Study participants also filled in a brief questionnaire, which we used to collect some demographic information such as their age, country of origin, and address within the dormitory. No explicitly identifying information was recorded, but BP device ID was included to link with. The study was approved by NUS-IRB-2021-92. The questionnaire can be found in Supplemental Material.

Each BP device sends a signal via Bluetooth technology every 7 min, which detects and records BP devices within a ∼3 m radius. Records of interactions were stored within the device for up to 9 weeks with a theoretical maximum of 8M records.

Classification of contact type

Because of the ongoing restrictions at the time of the study, MWs interacted relatively constrainedly, with workmates and roommates typically having longer and more frequent interactions, with interactions between individuals living on different floors or in different blocks being more random and of shorter duration. We therefore classify contacts into two distinct categories: regular and transient. A regular contact of an individual is defined to be their contact with whom the two individuals have interactions at least 4 days a week with each interaction lasting more than 15 min, following Singapore's Ministry of Health definitions.[26] A transient contact is defined when the criteria for the interactions do not meet this threshold (see Supplemental Figure S1).

*Description of the collected contact network (**G**)*

To investigate the occurrence of interactions across time, we presented the number of interactions (in an hour scale) each day of the week for regular contacts and transient contacts. To understand the exposure between MWs, the mean contact duration per day between two MWs was calculated. We also presented it in violin plots. We then summarised the mean number of contacts for regular and transient contacts across the study period and the mean contact duration per day among all MWs. The exposure time of each individual was formulated as the number of contacts that the MW had multiplied by the duration of interactions (hours) and is measured as man-hours.

Simulation of the contact network overlaying the two dormitories ($\mathcal{G}$)

Pairs of individuals were classified according to their proximity in the structure of the dormitory, defined by sharing the same room, a different room on the same floor, a different floor on the same block, or a different block in the same dormitory. We let $\phi_h = \{\phi_{hi}\}_{i\in I}$ denote the probability of a pair of proximity h settings (where h represents a distance type, that is room, floor, block, and dormitory; and I corresponds to the total number of rooms, floors, and dormitories accordingly) being classified as regular. We listed ϕ_h in Supplemental Table S2. A Bayesian hierarchical model for each degree of proximity was constructed as follows: Let y_i denote the observed number of pairs of regular contacts in the ith group (in a specific degree of proximity) and N_i the total number of pairs of possible contacts within the ith group. The joint posterior of $\phi_h,\ \alpha_h, \beta_h$ is therefore

$$p(\phi_h,\ \alpha_h,\ \beta_h|y) \propto p(y|\phi_h,\ \alpha_h,\ \beta_h)p(\phi_h|\alpha_h,\ \beta_h)p(\alpha_h,\ \beta_h)$$

$$= \prod_{i\in I} \phi_{h_i}^{y_i}(1-\phi_{h_i})^{N_i-y_i}\frac{\Gamma(\alpha_h+\beta_h)}{\Gamma(\alpha_h)\Gamma(\beta_h)}\phi_{h_i}^{\alpha_h-1}(1-\phi_{h_i})^{\beta_h-1}p(\alpha_h,\ \beta_h)$$

where α_h and β_h are the hyperparameters of the beta distribution associated with the degree of proximity h. The Metropolis–Hastings Markov Chain Monte Carlo (MCMC) algorithm was used to sample from the joint distribution. We ran a single MCMC chain with a run length of 100,000, with the first 10,000 samples discarded as burn-in. Geweke's convergence diagnostic was calculated for each chain. To simulate our regular contact network ($\mathcal{G}_R$), we built an adjacency matrix by drawing from binomial distributions using ϕ_h, obtained from the collected contact data, and information on the structure of the dorms (Table 1; MWs and their dormitory in Supplemental Material), sequentially filling in the number of contacts from the draws starting from the room level up until the dormitory level.

The same process was repeated for transient contacts, albeit with different estimates of the corresponding ϕ_h. The network of transient contacts is represented as $\mathcal{G}_T$.

Model structure and inference

The framework of the infection model assumes that physical interaction among MWs led to spread events via a branching process model (Figure 1).

To simulate the spread of COVID-19, a susceptible, infectious, recovered (SIR)-style model of individual-based contact networks was presented, and infected individuals became immune without being able to infect others at the time of the study. Branching process modelling was then

Table 1. Overview of the dataset.

	Dorm A	Dorm C
Layout distribution		
Number of blocks	6	3
Number of floors in each block	5	6
Number of rooms on each floor	8	12
Number of MWs in each room	20	16
Total number of MWs	4800	3456
Overview of collected data		
Number of participants	815	796
Number of participants with completed data entries*	520	491
Total interaction records included in the study	33.6M	52.8M

*Data entries include BP data extraction and questionnaire filling. BP: BluePass; MWs: migrant workers.

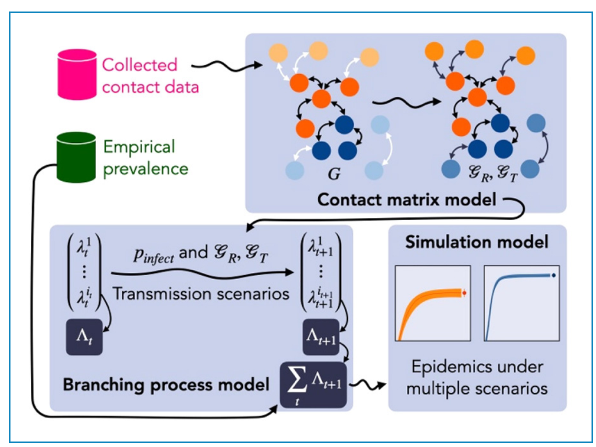

Figure 1. Model structure. Here, G and $\mathcal{G}$ represent the collected contact network and the simulated contact network, respectively. With the simulated contact network, we used a SIR-style branching process model to simulate daily cases (Λ_t) from day 1 to day 120 under different infection rates (p_{infect}), since the first wave of the outbreak in Singapore dormitories was about 4 months. We then looked for infection rates by individually matching cumulative cases simulated for different infection rates with reported prevalence. Thereafter, we simulated the epidemic scale of multiple intervention policies under these two scenarios, including a smaller outbreak (matching what was observed in Dorm A) and a larger outbreak (Dorm C). SIR: susceptible, infectious, recovered.

implemented to model new infections, corresponding to the matrices $\mathcal{G}_R$ and $\mathcal{G}_T$. Let I_t. be the collection of individuals infected on day t. Suppose that individual i was infected on day t_0, i.e. $i \in I_{t_0}$, and that individual j is a neighbour of i (if j is either a regular or transient contact of i). Then, on day $t > t_0$, i infects j with probability $p(t, t_0)$:

$$p(t,\ t_0) = \begin{cases} \min(\tau, t - t_0)\theta & \text{if } i \text{ and } j \text{ are regular contacts} \\ 0.009\min(\tau, t - t_0)\theta & \text{otherwise} \end{cases},$$

where τ is the infectiousness of i (see Supplemental Figure S2) and θ is the infection rate parameter. We also assumed that transmission to regular contacts and transient contacts differs by a multiplicative constant. The constant value of 0.009 was selected as it represents the ratio of interaction duration between regular and transient contacts, which was obtained from the collected contact tracing data. The error of the ratio is small (95% CI of this ratio is 0.0094–0.0096).

The previous prevalence study among MWs in Singapore found that the proportion of infected individuals during the course of the first wave was 56% (21), but this figure varied substantially from dormitory to dormitory, and so we explored a range of scenarios consistent with larger (66%) and smaller (33%) final prevalence. To determine the infection rate parameter θ that results in this proportion becoming infected, we first performed a grid search on the parameter $\theta \in (0,\ 1)$. We then fit the values of θ and the simulated infection proportion to obtain the relationship between θ and the infected proportion. The runtime of each simulated outbreak was 120 days, i.e. approximating the duration of lockdowns in 2020. A total of 1000 simulations were performed of each θ of the same contact network. The probability of becoming an initial case was assumed to be the same for each MW however. To make epidemic models under different θ comparable, we made all initial cases the same.

Simulation under non-pharmaceutical interventions

Using the infection rate values corresponding to the infection proportion of 33 and 66%, we simulated the interventions with multiple COVID-19 measures with 1000 simulations of the same contact network. The baseline scenario was to isolate all positive cases following a 1-day delay. The first alternative scenario was to quarantine all contacts with a 1-day or a 3-day delay, while the second alternative scenario was to quarantine all regular contacts with a 1-day or a 3-day delay, and the third alternative scenario was to lift case isolation and contact quarantine orders. Additionally, we simulated the epidemic size if a new dormitory was built to reduce the density of contact events in the existing dormitories. The length of isolation and quarantine was assumed to be 7 days, and the number of man-days lost to quarantine or isolation was tallied. More details of the multiple scenarios can be found in Supplemental Material (see Supplemental Table S3).

Results

The data of 1611 MWs (19.5%) were collected among the estimated 8256 MWs in the two dorms (815 in Dorm A and 796 in Dorm C). By the time of data extraction, 600 of their BP devices had experienced device failure (mostly from running out of power); these individuals were therefore excluded from the study. The remaining 1011 MWs with 82.7M interaction records were included in this study (Table 1).

Contact patterns from collected data

Participants were male, mostly aged 25–39 (60%), and most originated from South Asia: 47% were from Bangladesh and 37% from India; the remainder were mostly from Myanmar, Thailand, Malaysia, and China. We found no statistically significant differences in the mean number of contacts across age groups (ANOVA test P-value: 0.09) or their country of origin (ANOVA test P-value: 0.25). However, the contact type (regular versus transient; χ^2 test P-value < 0.001) differed significantly in terms of the average number of contacts observed (see Supplemental Table S4).

We found no evidence of age-based assortative mixing. However, there was evidence of assortative mixing by country of origin, with those originating from China, Myanmar, Bangladesh, and other countries (not India) spending more time with those from their same country of origin for both regular contacts and transient contacts; Indians had assortative mixing with other Indians and Myanma people (see Supplemental Figure S3). We also found that MWs who had regular contacts with the same group of MWs interacted with them almost daily (81%), whereas with transient contacts, most interacted across different groups of MWs, mainly on a weekly or monthly basis (see Supplemental Figure S4(b)).

In addition, there were no notable trends in interaction event behaviour on different days of the week (WAVK test[27] P-value of regular contacts: 0.18; WAVK test P-value of transient contacts: 0.55). However, there were strong hourly trends (WAVK test P-value of regular contacts: 0.01; WAVK test P-value of transient contacts: 0.01). The peak for interactions of regular contacts was between 18:00 and 06:00 daily, which is the typical resting time for MWs. In contrast, the peak time of interactions of transient contacts was at the time of mass transportation to and from work and on their lunch breaks (see Supplemental Figure S5).

For interaction duration in a day, when compared to transient contacts (mean: 5 min), regular contacts (mean: 7 h 3 min) spent significantly longer periods together (P-value

< 0.001). The details of interaction duration within a day can be found in Supplemental Material (see Supplemental Figure S6). Furthermore, we found that regular contacts usually occurred with people sharing the same room, and transient contacts occurred between individuals of different dormitories, blocks, or floors. The mean interaction duration in a day within the same room of regular contacts was 8 h 52 min; shorter durations of interaction events happened for contacts within the same floor and same block. There were few regular contacts with relatively short interaction duration in the same dormitory but not in the same blocks and between different dormitories. The duration of transient contact interactions was on average 8 min for each interaction; multiple interactions between transient contacts were observed, particularly for those in the same unit, totalling 53 min over the typical day in multiple short spells (Table 2).

Simulation of the contact network of the whole population in study dormitories

According to the likelihood of contact within the different degrees of proximity (room, floor, block, and dormitory) obtained from the collected contact data, we simulated the contact network among 8256 MWs in two dormitories. There was a mean number of regular and transient contacts per individual of 13 and 168 (Figure 2), respectively, with most of the former being individuals sharing the same room and floor of a block, similar to the empirical data (see Supplemental Table S4).

Simulation of the epidemic size under multiple non-pharmaceutical interventions

The simulated dormitory outbreak ran for 4 months (the final attack rates were similar when extended to 6 months; see Supplemental Figure S7(b)). To obtain infection rates that match the empirical final attack rates in the two dormitories (33 and 66%), we required an infection risk per person throughout the course of infection of 0.4 (for Dorm A) and 0.87 (for Dorm C) (see Supplemental Figure S7(a)).

Using an infection rate of 0.40 to represent a smaller outbreak and 0.87 for a larger outbreak, we then investigated the effects of intervention strategies on the epidemic size at 120 days under multiple non-pharmaceutical interventions (NPIs): baseline where only positive cases are isolated, quarantining of regular contacts, quarantining of all contacts, and no isolation and quarantining at all. All were run with and without delay in case identification. The impacts of notification delay are presented in Supplemental Material (see Supplemental Figure S9). For the baseline scenario with a less infectious variant, 31% (95% CI: 28–41%) of the total resident population across both dormitories would be infected by day 120 (Figure 3(a)) while losing 22,064 man-days accordingly. When all contacts were immediately quarantined, the infected proportion decreased substantially to 1.1% (1–1.3%) (Figure 3(b)) as 66,667 man-days would be lost accordingly. When only regular contacts were immediately quarantined, the proportion was also low at 6% (5–8%) with 35,504 man-days lost (Figure 3(c)). Without any isolation or quarantining, the proportion is at its highest at 41% (31–47%) (Figure 3(d)). In a lager outbreak, 67% (62–68%) of the whole resident population were infected under the baseline scenario with 38,892 man-days lost (Figure 3(f)), decreasing to 33% (28–35%) when only regular contacts were quarantined with 87,500 man-days lost accordingly Figure 3(h)) and to 3.8% (3.3–4.3%) when all contacts were quarantined with 112,496 man-days lost (Figure 3(g)). In contrast, the proportion of getting infected was high at 72% (71–73%) when no quarantining or isolation was implemented at all (Figure 3(i)).

To further investigate the impact of resident density, we reduced the number of social contacts of each resident by moving 30% of residents to a hypothetical new dormitory. The proportion of infected individuals was substantially lower at 19% (15–24%) for the baseline scenario with a θ of 0.4 (Figure 3(e)) and 57% (51–61%) when θ was set at 0.87 (Figure 3(j)).

Discussion

DCT data can be coupled with infectious disease models to simulate the spread of disease. In this study, we utilised a branching process model and simulated a contact network derived from empirical social interaction data to model an epidemic outbreak in a closed population. The heterogeneous mixing at different infrastructural levels was captured based on the data collected from portable Bluetooth devices, revealing group-based contact patterns and relations within the dormitory hierarchy in which transmission risk may be elevated. The effectiveness of various NPIs designed to reduce the risk of transmission through blocking certain interactions was investigated using our model. Through understanding viral spread in closed high-density settings, more informed planning for future outbreaks can be carried out.

We found that the severity of the outbreak between the two study dormitories is significantly different. The infection rate was lower in Dorm A than in Dorm C.[28] It could be plausible that Dorm A, which is laid out more in the style of sparser populated apartment blocks, had less environmental transmission when compared to the barrack style of Dorm C. To show this, we simulated the epidemic size with a reduced overall number of contacts by 30%, decreasing infection rates from 31 and 67% to 19 and 57% for a more and less infectious pathogen, respectively. This indicates that reducing resident density, potentially through

Table 2. Summary of regular and transient contacts in a day.

Items	Group	Regular: Mean number of contacts/day	Regular: Mean contact duration/day*	Transient: Mean number of contacts/day	Transient: Mean contact duration/day*
Overall		5	7 h 3 min	26	5 min
Dormitory setting					
	Same unit	2	8 h 52 min	1	53 min
	Same floor only	1	6 h 10 min	4	12 min
	Same block only	1	5 h 42 min	7	5 min
	Same dormitory only	0.5	4 h 22 min	7	1 min
	Different dormitories	0.5	3 h 02 min	7	2 min

*Interaction duration per day is calculated by summing up all interactions within a day with the same individual over possibly multiple interactions. The mean interaction duration of regular encounters and transient encounters was 53 and 2 min in a day, respectively.

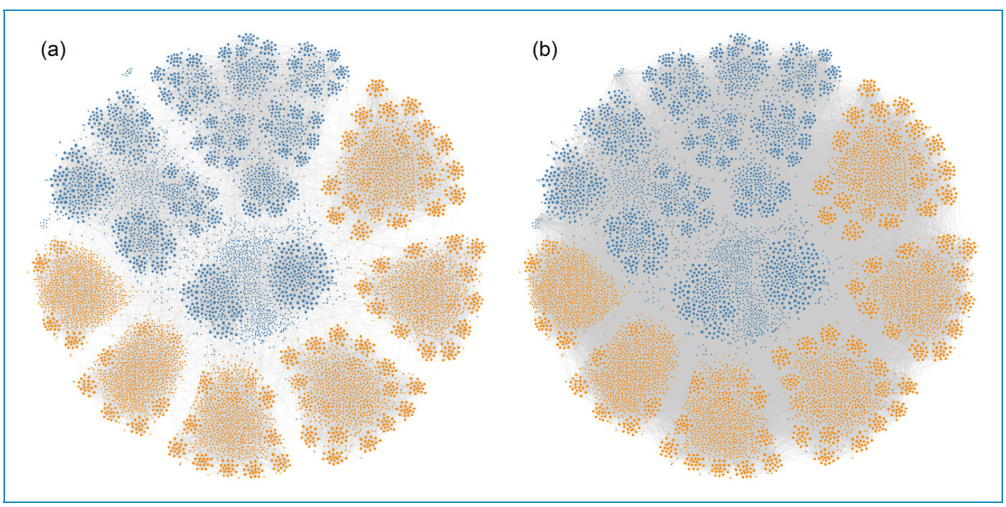

Figure 2. Simulated contact network. Regular (a) and transient contacts (b) for Dorm A (dark orange) and Dorm C (steel blue).

the construction of new dormitories, could substantially lower the risk of rapid infectious disease spread when new outbreaks emerge.

In the face of rising cases, lockdowns are critical tools that can reduce the spread of a respiratory virus in closed settings. However, costs can be exceedingly high when the virus is highly transmissible[29] due to the containment measures required to ensure compliance, often bringing additional mental health burdens to the residents,[30–32] and despite ongoing efforts at containment in China, these measures do not seem sustainable in other settings. Our simulation results indicate that the quarantining of all or regular contacts can substantially reduce outbreak size, but such methods should be used at the beginning of new outbreaks or when the risk of the illness developing severe complications warrants such constrained measures for the residents, such as the implementation of lockdowns in Wuhan city[33,34] and other cities and territories/countries early in the COVID-19 pandemic.[35] Notably, there is a difference between the baseline of only isolating cases and no control at all at 10% for an infection rate of 0.4 and 5% for an infection rate of 0.87. In a latter part of an outbreak, the

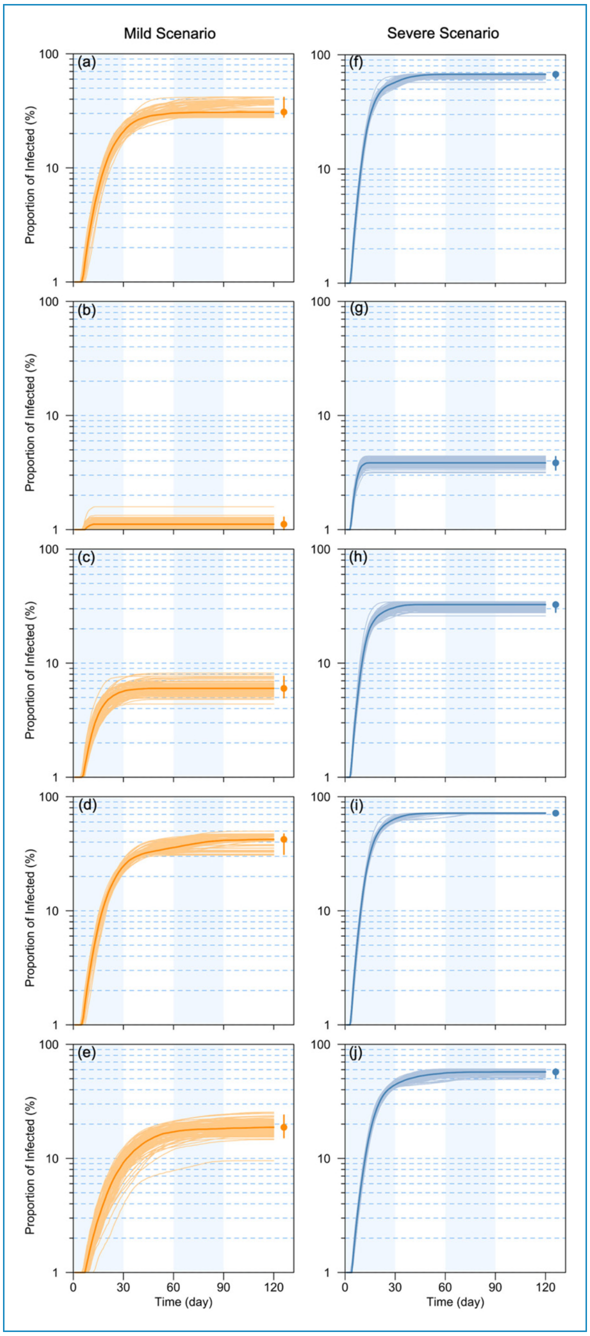

Figure 3. Simulation of the epidemic size under multiple NPIs under smaller and larger outbreaks (i.e. with θ of 0.4 and 0.87). (a) and (f) Scenario 1: Immediate isolation of cases in the baseline scenario. (b) and (g) Scenario 2: Immediate isolation of cases and quarantining for all contacts. (c) and (h) Scenario 3: Immediate isolation and quarantining of regular contacts. (d) and (i) Scenario 4: No isolation of cases or quarantining of contacts. (e) and (j) Scenario 5: Baseline scenario under a 30% reduction in contacts. Daily cases of the epidemic can be found in Supplemental Figure S8. NPIs: non-pharmaceutical interventions.

isolation of cases may therefore bring relatively few benefits to the population as a whole, as the majority have already been infected. Nevertheless, mass testing is strongly recommended and individuals should be given a choice to self-isolate if they are positive or wish to, as they have been suspected of being exposed.[36]

The simulations revealed that a policy of quarantining regular contacts only would be relatively efficient in reducing infections with relatively little impact on the number of people being quarantined. In contrast, quarantining all contacts would be necessary to prevent epidemic spread, but due to the large number of casual contacts in a high-density living environment such as those considered in this paper, such a policy would lead to large numbers of people in quarantine, and without long-term means of preventing spread, such quarantine would need to be implemented over too long a time period to be feasible.

Overall, the use of Bluetooth technology via wearable devices such as BP is useful when modelling epidemic sizes under different quarantine orders, which is critical information for policymakers in their planning efforts for closed settings, especially ones with low vaccination rates. Having stand-alone Bluetooth devices can overcome the disadvantages of common digital communication technologies,[37] as such devices do not require any modification to an individual's mobile cellular device to incorporate contact tracing functioning, which reduces the perceived level of intrusion and may encourage participation. Moreover, all BP devices are secure, with the devices de-identified and social interaction records encrypted before being stored locally on each device, so that data retrieval is only possible by accessing the memory storage of the device. In our study, this was obtained by physical extraction, but this was a labour-intensive endeavour that could not be sustained in routine use.

The study has its limitations. We had the assumption that the likelihood of transmission of SARS-CoV-2 was proportional between the two contact categories with transmission to transient contacts occurring at 0.009 times that of regular contacts. This was determined through the proportion of regular and transient mean interaction durations from the DCT data obtained from BP devices. While we know that the risk of transmission decreases with shorter verbal conversations,[38] this could be an underestimation of transmission likelihood if individuals are being infected through surfaces and fomites. In addition, the contact networks we observed were only for a period in which residents were able to leave their dormitory for work and in some other limited circumstances for other purposes, and the structure of the network may have been more active than contact patterns in the early and later stages of the pandemic. However, MWs still need to get approval when they leave their dormitory for personal purposes during the data collection period. Also, we assumed that MWs had the same probability of being the initial case in our simulation model. Factors such as heterogeneous mixing and contact behaviour for MWs could not be incorporated for initial cases as this information is largely unknown.

Despite these limitations, using DCT devices was able to investigate heterogeneities in contact within the networks of a closed environment, which has implications for how epidemics spread. The impact of various policies on SARS-CoV-2 transmission can be explored, feeding into policymaking decisions on how to prevent future outbreaks of respiratory illnesses in high-risk closed environments where epidemics can rapidly take hold and spread.

Acknowledgements: The research was supported by the help and technical training of Bhagya Gunaearchrathne Perera of D'Crypt, who facilitated data extraction from the BluePass server. Data collection was possible thanks to the efforts of Amanda Low, Aysha Farwin, Crystal Chua, Haoyang Sun, Jie Sun, Rayner Tan, Sharon Quaye, Ligo Val Alvern Cueco, Yinan Mao, and Zitong Zeng from Saw Swee Hock School of Public Health, NUS. We are also grateful to Zaw Myo Tun, Shweta Rajkumar Singh, and Kyin New Moong Don for their help with translation. Finally, we would like to thank the staff in the dormitories, especially Shahul Hameed and Richard Lim, and their colleagues, for helping to facilitate the data collection process, and the participants themselves for their kind forbearance.

Contributorship: YS and JRK conducted the analysis. YS wrote the manuscript. ARC, BD, HY, JRK, MP, and YS organised the fieldwork for data collection (on-site). ARC, BD, and JRK refined the manuscript. ARC and HY conceived the study.

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Declaration of Conflicting Interests: The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical Approval: NUS-IRB approved this study (IRB Number: NUS-IRB-2021-92).

Funding: The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by Temasek Foundation and iHealthtech at the National University of Singapore.

Guarantor: ARC and BD.

Supplemental Material: Supplemental material for this article is available online.

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