~~Effects of~~ Temporal Factors in School Closure Policy for Mitigating the Spread of Influenza

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ABSTRACT

It has been under debates whether school closure is effective in mitigating the outbreak of influenza. To better address the problem, we develop an individual-based simulation model based on the real-life contact data in Singapore. By conducting extensive simulations on the model, we evaluate the impacts of temporal factors, namely the trigger threshold and duration, on the effectiveness of school closure as a mitigation policy. Our observations show that there exists an upper bound of the duration of school closure, further extension beyond which will not bring additional benefits to suppressing the attack rate and peak incidence. We also show that, for school closure with a relatively short duration (< 6 weeks), it is more effective to start it with a relatively longer delay from the first day of infection; if the duration of school closure is long (> 6 weeks), however, it is better to start it as early as reasonable. Our studies reveal the critical importance of timing in school closure, especially in cost-cautious situations. The studies also demonstrate the great potential of a properly developed individual-based simulation model in evaluating various disease control policies.

Keywords: School closure policy, temporal factors, influenza, public health

I. INTRODUCTION

The 2009 H1N1 pandemic has caused world-wide concerns on public health. Diversified intervention strategies had been planned and implemented in different countries and continents [1-4]. Although the pandemic finally ended with mild health impacts, it challenges people to think about the crucial control strategies for mitigating the spread of an emerging virus which may cause high morbidity and mortality in the communities, especially when pharmaceuticals are not available or in shortage yet a substantial number of infected cases have been reported.

Schools are one of the crucial community structures in epidemic control and mitigation planning. High contact rates and long contact durations in schools prompt the disease spreading among the school population. School closure, as a conventional non-pharmaceutical intervention [5], has been extensively evaluated and even implemented in real-life disease control. However, its effectiveness is still under debates [6-9]. In a recent article, Cauchemez et al. [10] reviewed multiple aspects of school closure and concluded that there exist many uncertainties in the benefits of school closure as a mitigation method. The historical data of real-life implementations of school closure also reveals contradictory conclusions. In March 2008, Hong Kong school officials made an abrupt decision to close all primary schools for 2 weeks, as an effort to block a rising wave of seasonal influenza, only to be later reported as having no substantial effects [11]. On the other hand, Israeli school closure data from January 16 to January 28 in 2000 supported the effectiveness of school closure in reducing respiratory infections [12]. It is noted that the evaluations on school closure were concluded in different social structures which may affect the effectiveness of the policy significantly. Besides the differences in social structures, we believe that the divergent conclusions also partly come from the different temporal factors in these implementations, specifically the trigger threshold (when to close schools) and intervention duration (how long to keep schools closed). In this paper, we test different cases of school closure with different trigger thresholds and durations, including the uncontrolled scenario. Comparing simulation results of these cases, we explore the impacts of temporal factors on the effectiveness of school closure in mitigating the spread of influenza epidemic.

The methodology adopted in this study is as follows. We construct an individual-based simulation model based on the real-life social contact data of Singapore, and then evaluate the effectiveness of school closure on this model. The realistic modeling of the social-contact network allows the complex heterogeneous social structures to be properly revealed [13-15]. By representing people (or places) as “vertices with contacts”, computer programs can easily simulate the transmission of infectious diseases through individual interactions along the links within the contact network. Such a method is more intuitive than mathematical modeling and advantageous in visualizing the spreading dynamics of infectious diseases. It also enables detailed evaluations on the effects of different temporal factors in various scenarios.

The rest of this paper is organized as follows. Section II introduces in detail the construction of the social contact network and defines the models of disease spreading and intervention policies. Extensive simulation results are reported in Section III, followed by further discussions in Section IV. Section V concludes the paper.

II. Method

In this work, we run individual-based simulations on a realistic social contact network model. The network is constructed by adopting the real-life data of Singapore communities. The contact network represents the statistical properties of interpersonal contacts which can potentially lead to disease transmission. By conducting extensive simulations on the network model, we investigate the effectiveness of school closure with different trigger thresholds and implementation durations.

A. Contact Network Construction

Contact network is a network representation of human-to-human contacts in a community. Each person is represented by a vertex in the network and each contact between people is represented by an edge connecting the pair of vertices. The pathogens of the disease transmit from one person (vertex) to another (vertex) only through the connecting edges. The number of edges emanating from a vertex is the *degree* of the vertex. The distribution of the degrees of vertices, also called *degree distribution*, is a fundamental quantity in network theory, playing a critical role in estimating the outbreak size and epidemic probability of a network [13].

Most social contacts take place in various community structures such as schools, workplaces, hospitals, etc (Figure 1). In the network's perspective, community structures can be represented by *clusters* of vertices which have denser connections internally than outside. The existence of clusters significantly affects the topology of contact network and the transmission of diseases on it [16].

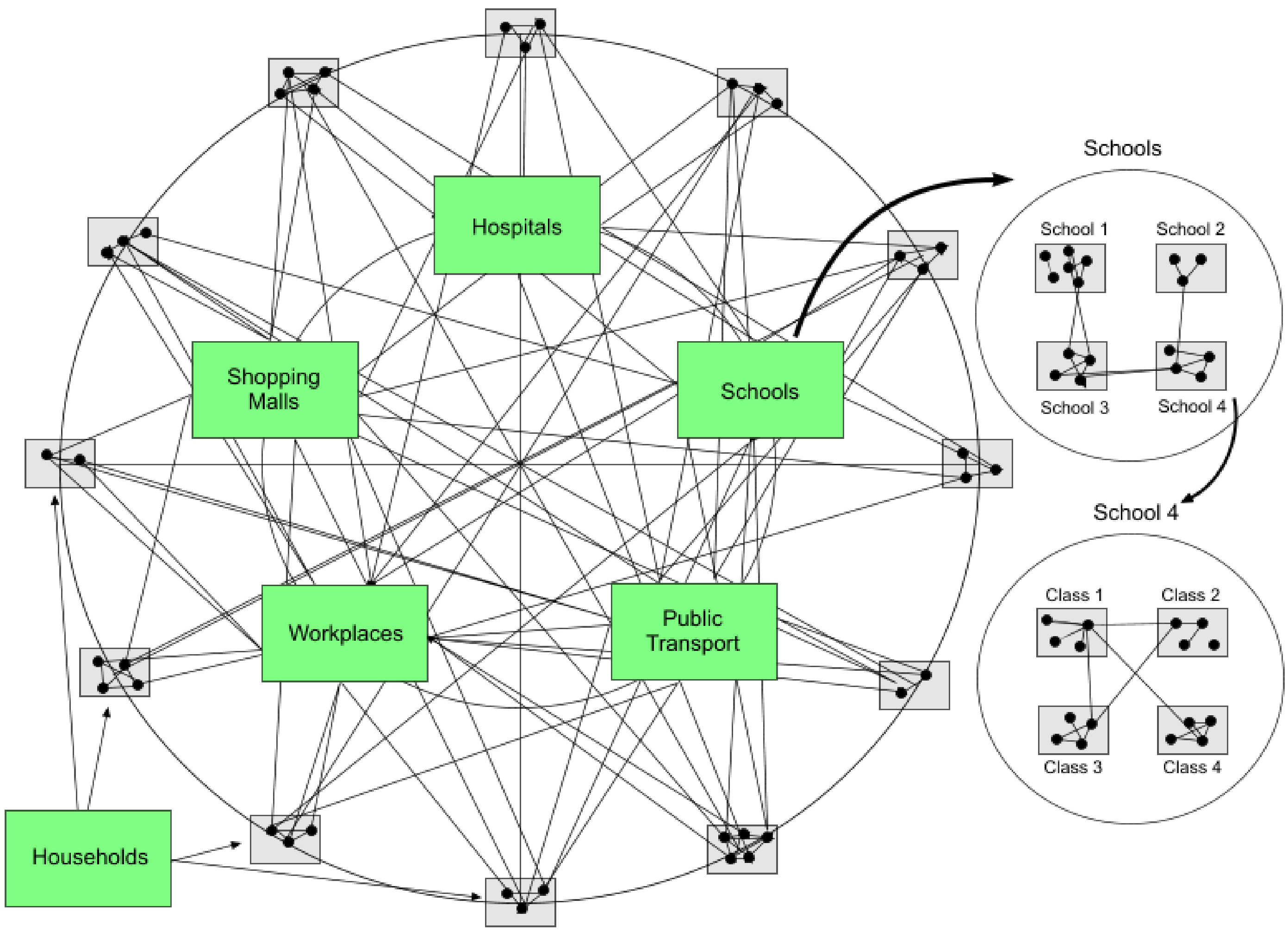

Figure 1 Schema of contact network in the urban setting. Dots denote people and lines connecting between dots denote the interpersonal contacts that may lead to disease transmission.

Using HPCgen model [17], we construct a plausible contact network based on Singapore social structure. We set up 100,000 households according to Singapore household size distribution, household structure and age distribution [18], which yields approximately a population of 480,000. According to household members' ages, they are assigned to occupy the schools and workplaces by following the school size distribution and company size distribution in Singapore. The individuals are also assigned to visit other community structures such as shopping places and hospitals based on shopper traffic statistics and ward bed occupancy records. Public transport is vital for the commuters in a densely populated city like Singapore, with daily ridership up to 5,000,000 passenger-trips in 2008/09 [19]. We assume public transport as a giant community structure in which all the commuters are mixed to make contacts randomly. Within each community structure, we create the random connections between pairs of individuals by assuming a Poisson degree distribution [15] with the mean degrees acquired from our surveys on social contacts. Each school and hospital is further divided into sub-units, i.e. classes and wards. Each individual in the sub-units is assumed to have a higher probability to contact with someone from the same sub-unit than from the other sub-units. Teachers and healthcare workers are also assigned to the classes and wards to contact with students or patients. The list of applied data and their sources are tabulated in Table 1.

Table 1 Data for constructing contact networks (All data was acquired from Singapore)

Community Structures	**Data**	**Source**
Households	household size distribution, household structure	1) department of statistics 2) survey
Hospitals	hospital and ward size distribution, contact rate, caregiver allocation	1) local hospital
Schools	school and class size distribution, contact rate, teacher allocation	1) ministry of education 2) survey
Workplaces	workplace size distribution, contact rate	1) ministry of manpower 2) survey
Shopping Places	visitor traffic, contact rate	1) local shopping mall 2) survey
Public Transport	commuter traffic, contact rate	1) land transport authority 2) survey

To our knowledge, there has been no prior study on contact behaviors in regard to infectious disease spreading in Singapore. To have a better estimation of the number of contacts at different locations, we conducted the social surveys to the public in Singapore in year 2008. There are totally 1040 pieces of survey data collected. The derived average numbers of contacts are summarized in Table 2. The average number of contacts in the households is excluded in the table as we assume every household as fully connected.

Table 2 Average numbers of contacts in different types of locations.

Community Structure	Average Number of Contacts
Hospital	5.83
Ward	9.12
School	18.02
Class	29.65
Workplace	20.55
Shopping Place	21.21
Public Transport	18.48

B. Models of Disease Spreading

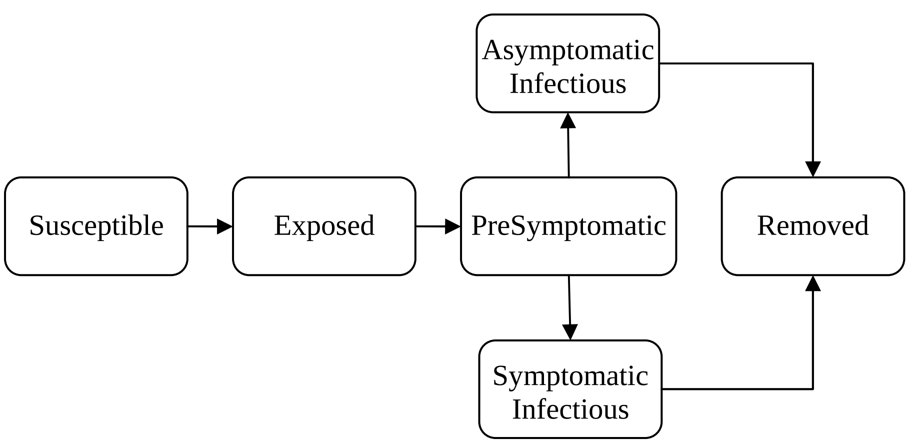

Figure 2 Dynamics of influenza progression within host individuals.

Spread of influenza is comprised of two portions: infection and host progression. *Infection* is the process that an infectious person infects his/her susceptible contacts; and *host progression* is the process of infectivity development of influenza illness within the host person (

Figure 2). By making contacts with infectious individuals, a susceptible has a chance (transmission probability) to be *exposed*, i.e. infected by the influenza virus; then after the period of latency, the *exposed* person becomes infectious but has not yet developed any symptom, termed *pre-symptomatic*; until incubation period since exposed, the *pre-symptomatic* person has a probability (symptomatic rate) to develop the clinical symptoms of influenza and turns into *symptomatic infectious*, or stay as *asymptomatic infectious* without any symptoms; finally after the rest of infectious period elapses, the *symptomatic or asymptomatic infectious* person is *removed*, i.e. either recovered from influenza or dead.

C. Intervention Policies

There are different types of school closure: 1) class closure, e.g., a class is closed if there is a diagnosed case; 2) individual school closure, e.g., a school is closed if there are diagnosed cases, and 3) all-school closure, i.e., all schools are closed simultaneously if a threshold number of cases are diagnosed. All three types of school closure had been implemented in the real-world interventions in different countries including Australia, UK, USA, and Japan to mitigate the spread of pandemic influenza [13-15].

In this study, we implement all-school closure in the simulations with varying trigger thresholds and implementation durations. We assume: *1) all schools are closed immediately once the trigger threshold is reached; 2) all the contacts taking place in schools are removed from the contact network during the period of school closure; and 3) school closure does not cause an increase of contacts in other community structures*.

Besides modeling the dynamics of the disease spread, the focus of this study is on investigating the effectiveness of intervention polices in different scenarios. We parameterize an intervention policy by two parameters: *trigger threshold* and *duration*:

- *Trigger threshold* is a percentage of diagnosed (symptomatic) cases in the overall population, which is used to determine the starting time of intervention. For example, trigger = 0.1% means an intervention will be implemented when 0.1% of population is diagnosed.
- *Duration* refers to how long an intervention will be implemented.

III. Results

We first simulate the uncontrolled scenario on the constructed contact network, which contributes the baseline results. Then we simulate all-school closure with different trigger thresholds and durations, to evaluate their impacts on the effectiveness of school closure.

A. Experiment Settings

The basic reproductive number, R_0, is defined as the average number of secondary infections produced by a randomly selected infected person in a fully susceptible population [20]. We determine R_0 empirically by assuming a scenario in which only a single randomly selected individual is infected and everyone else is susceptible and not able to transmit, and then count the average number of secondary infections. R_0 is then obtained as the average number of secondary infections in 10,000 realizations. In our simulations, R_0 is estimated to be 1.9 (95% CI, 1.871 – 1.924) and the mean generation time (T_g) is 2.522 days (95% CI, 2.489 – 2.508), which are comparable with estimates of R_0 = 1.4 – 2.3 and T_g = 1.3 – 2.71 days for the 2009 influenza pandemic [21,22]. We use 66.7% of symptomatic rate [23] in the simulations, and assume that one third of the generation time is uninfectious (latent) [21]. The base transmission probability is 0.04, at which an infectious person may infect his/her susceptible contacts; the transmisson probability is doubled if the person is symptomatic infectious, and meanwhile, half of the contacts is randomly removed due to self-isolation or self-shielding.

Each of the simulation scenarios, including the baseline case, runs for 200 days and iterates for 100 times. All the results reported in the following section are average values of the 100 simulation runs. Every simulation starts at *day* 0 with 10 infectious persons randomly seeded into a susceptible population without prior immunity to the influenza virus. The modeled population is assumed as a closed system, meaning that there are no people flowing into the system and consequently no newly imported cases. In our experiments, there are four candidate trigger thresholds (0.02%, 0.25%, 1.5% and 5%) and five implementation durations (2, 4, 6, 8, 10 weeks) for creating an intervention scenario, leading to a total of 20 different scenarios. In addition, three more scenarios have also been simulated, including the uncontrolled epidemic, and two scenarios for evaluating the impacts of higher trigger thresholds (10% and 15%) for a short school closure (2 weeks).

The effectiveness of interventions is examined by evaluating *attack rate* (*AR*), *peak incidence* (*PI*), and *peak day* (*PD*). *Attack rate* refers to the cumulative proportion of symptomatic cases of influenza infection in the overall population; *peak incidence* refers to the highest number of the daily incidence of symptomatic cases; and *peak day* refers to the day when the peak incidence happens. In the public health perspective, attack rate indicates the size of epidemic and the overall burden on the public health system due to an epidemic; and peak incidence and peak day display the challenge to public health system in response to patient surges.

B. Dynamics of Influenza Spread without Intervention

Figure 3 shows the results of the uncontrolled scenario. The epidemic reaches its peak on *day* 26 and fades out on *day* 73. The total attack rate is 44.47% (95% CI, 44.45% - 44.48%); peak incidence is 42.45 per 1000 people (95% CI, 41.72 – 43.17); and the peak day is *day* 26. This result is comparable with 43.5% attack rate found by Germann et al [24]. It is noted that the trigger thresholds {0.02%, 0.25%, 1.5%, 5%, 10%, 15%} are reached on *day* {7, 13, 17, 20, 22, 24}, respectively.

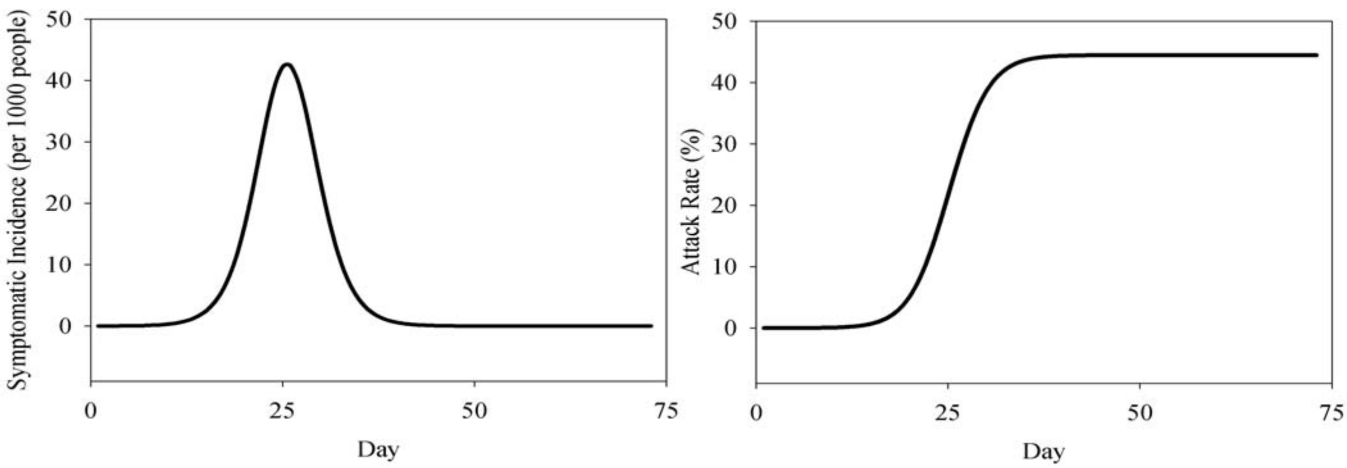

Figure 3 Daily incidence and average attack rate of the uncontrolled scenario in 100 runs (R_0 = 1.9).

C. Impacts of Temporal Factors on All-School Closure

Figure 4 shows the effects of trigger thresholds and durations on the attack rate in all-school closure. The attack rates after implementing school closure are in the range of 40.42% to 44.45%, with a 0.05% to 9.10% reduction compared to that of the baseline case. The lowest attack rate occurs when 10-week school closure is triggered at 0.02%.

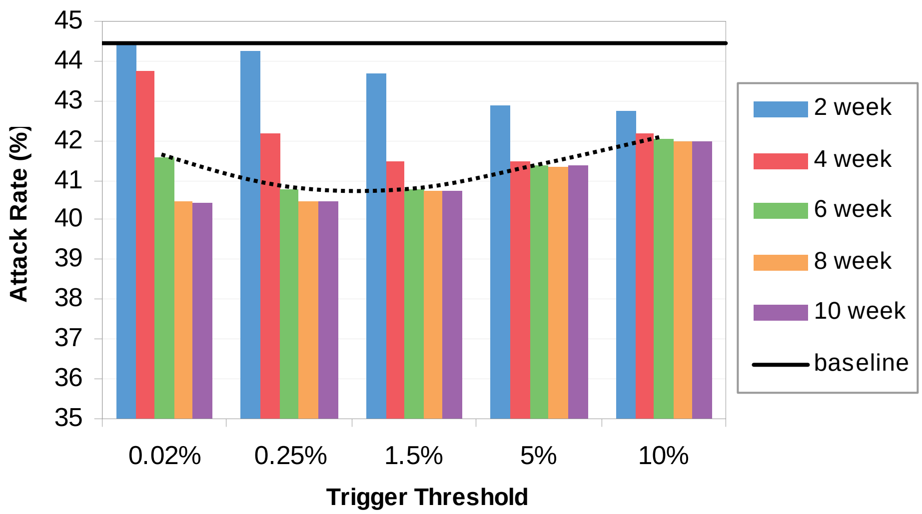

Figure 4 Attack rate with all-school closure. Attack rates for 6-week closure have a shape of convex curve (dotted line).

It is easy to follow that the longer intervention duration leads to a lower attack rate. We note that a 8-week all-school closure are sufficient in our settings as further extending the duration of closure does not reduce the attack rate significantly. In addition, the influences of trigger threshold show an interesting pattern: if the duration < 6 weeks, having a higher threshold leads to a lower attack rate; if duration > 6 weeks, a rising threshold results in a slightly higher attack rate; if the duration = 6 weeks, a convex shape appears as shown in Figure 4.

It can be understood that a short period of closure may be more effective if it is implemented at reasonably higher thresholds (before the epidemic peak) when more infectious patients exist in the population. That is because a larger number of potential infections could be blocked due to contact removal. Our results show that the 2-week closure is the least effective one, and its impacts are only noticeable when it is triggered at 1.5% and above. 4-week closure is able to influence the attack rate when it is triggered as early as at 0.02%, and a steady decline in attack rate is observed when its threshold rises. When the closure is sufficiently long (> 6 weeks), however, significant impacts can always be achieved as contact removal can be maintained until the late stage of the epidemic. To achieve a more significant reduction in attack rate or peak incidence, it is advisable to start the long-duration closure as early as reasonable. At the cutoff point, the attack rates for 6-week closures have a shape of convex curve, showing the existence of both trends.

Earlier we showed a trend that having a higher threshold will cause a lower attack rate if the closure duration < 6 weeks. It is interesting to further find out the upper bound of the threshold at which the trend is still valid. We show two extra scenarios where 2-week school closure is triggered at the thresholds of 10% and 15%, respectively. In Figure 5, 2-week closure at 15% threshold leads to a higher attack rate than the those at lower thresholds (5% and 10%), which does not follow the trend anymore. Instead, a convex function is again observed, only that the minimum attack rate is achieved at a rather high trigger threshold of about 10%, probably too high to be acceptable for real-life implementations.

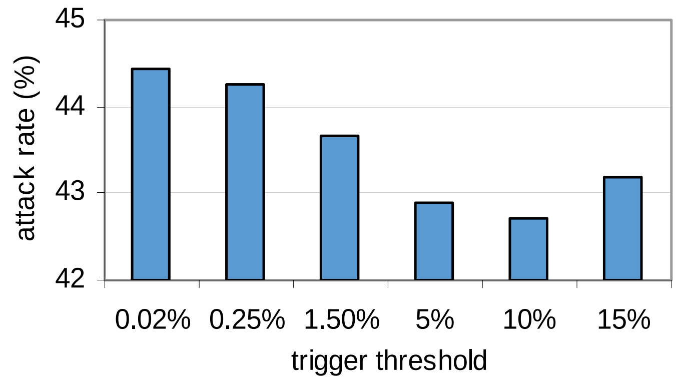

Figure 5 Attack rate with all-school closure. Attack rates for 2-week closure also have a shape of convex curve.

The simulation results could help provide the suggestions for different needs. For cost-cautious reason, policy makers may prefer shorter intervention. For such case, it is recommended to start school closure with a relatively longer delay since outbreak; if policy makers aim for minimizing the size of epidemic, they should implement school closure as early as reasonable and last for more than 6 weeks. We also note that, for intervention with a shorter duration, it is more important to make a wise choice of trigger threshold. For example, for 2-week school closure, it could save extra 6.05% of the overall population from infection at no additional cost by properly choosing the trigger threshold.

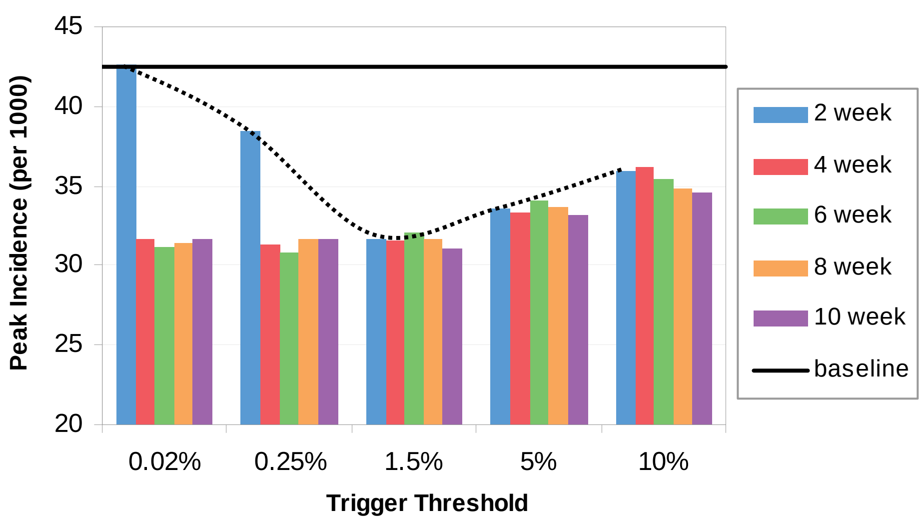

Figure 6 Peak incidence with all-school closure. Peak incidences for 2-week closure has a shape of convex curve (dot line)

Figure 6 shows that all-school closure significantly reduces peak incidence of the epidemic. The lowest peak incidence under school closure is 30.75 per 1000 people, a 27.55% reduction compared to that of the baseline case. It is achieved when 6-week closure is triggered at 0.25%. Note that 4-week closure is sufficient for reducing the peak incidence as the extended closure does not bring in any significant benefit on easing the worst-case stress on public health systems. The influence of trigger thresholds on peak incidence exhibits the similar trends as discussed earlier: if duration > 2 weeks, a rising threshold results in a slightly higher attack rate; if duration = 2 weeks, the peak incidences have a shape of convex curve.

Figure 7 reveals that all-school closure steadily delays the peak day. Specifically, it can be observed that the peak day is significantly affected by trigger threshold, but not by duration. When the threshold rises from 0.02% to 5%, peak day steadily moves earlier. The longest delay obtained is 5 days compared to the baseline. It is achieved when any closure longer than 2 weeks is triggered at 0.02%.

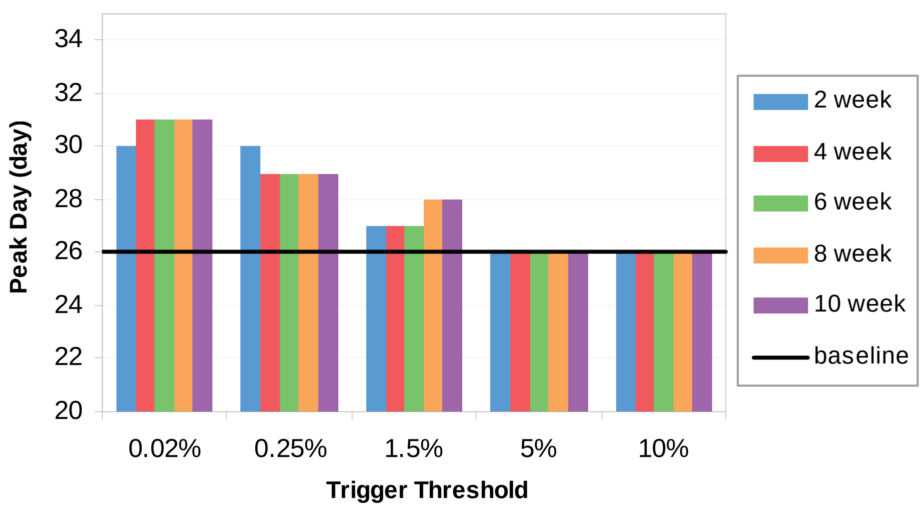

Figure 7 Peak day with all-school closure

D. Validation of Conclusions under Different Transmission Rates

We have observed the interesting patterns of how epidemic measures are influenced by temporal factors when R_0 = 1.9. To evaluate whether the observations remain valid in social systems exposed to different virus strains, we perform simulations with different values of R_0 at 1.5 and 2.3 respectively. The new simulation results demonstrate consistent patterns as observed in earlier sections.

Figure 8 shows the attack rates under all-school closure when $R_0 = 1.5$. Similar as that when $R_0 = 1.9$, the attack rate drops when the trigger threshold rises from 0.02% to 5% if the duration is less than 6 weeks. If duration is longer than 6 weeks, the attack rate may increase rather than decrease once the trigger threshold is higher than a certain value. The attack rates show as convex functions of trigger threshold in different cases where school closures last for 6, 8 and 10 weeks, respectively.

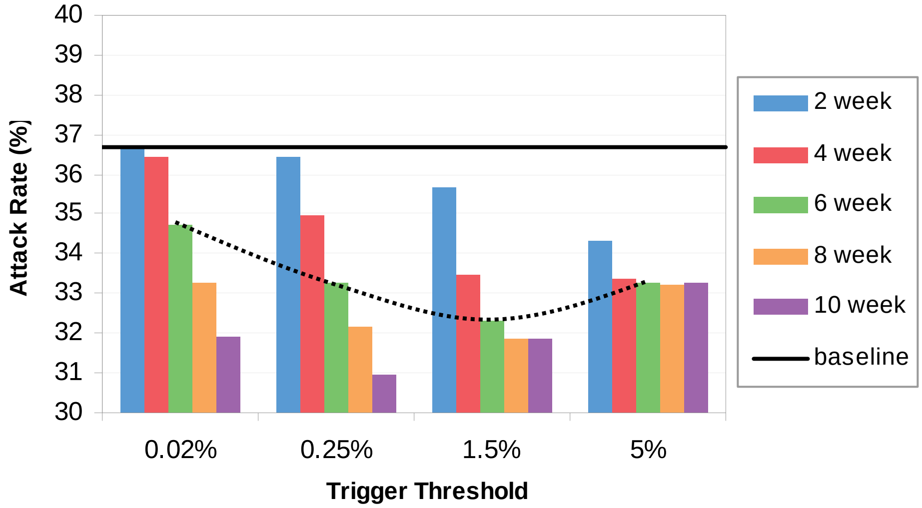

Figure 8 Attack rate with all-school closure ($R_0 = 1.5$). Attack rates for 6, 8 and 10-week closure all appear to be convex functions of trigger threshold. The dotted line highlights the results for 6-week closure.

Figure 9 echoes the findings in Figure 8. It is clearly shown that, when trigger threshold rises, the attack rates decrease for 2-week closure and increase for 6-, 8- and 10-week closures. At the cutoff value of 4-week closure, the attack rates clearly form into a convex function of trigger threshold.

Though it is impossible to numerically evaluate all the possible different scenarios, the above results suggest wide applicable range of our conclusions.

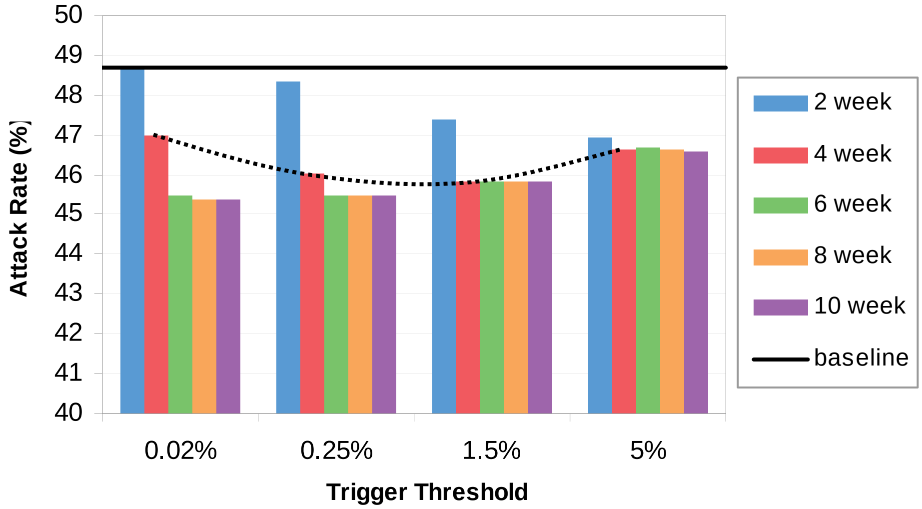

Figure 9 Attack rate with all-school closure (R_0 = 2.3). Attack rates for 4-week closure have a shape of convex curve (dot line)

IV. Discussion

School closure is a social distancing measure which aims to reduce disease-causing contacts between individuals. As the production of vaccine and stockpiling of anti-viral drugs usually takes considerable time, the shortage of pharmaceuticals is always a challenge in the preparedness plan for pandemic influenza. Social distancing measures are necessary complements to the pharmaceutical interventions, especially when a novel strain of influenza emerges with a high transmission rate.

Our simulation results have shown that school closure helps lower attack rate and daily incidence and delay the peak day in most intervention scenarios. Our observations show that under a cost-cautious situation in which short intervention is preferred, all-school closure should be implemented at a higher threshold (a later time); if reducing the epidemic size is the top priority, it is advisable to implement a longer school closure (more than 6 weeks) as early as reasonable to enjoy the benefits of a lower attack rate, a smaller peak incidence and the delayed peak day. Moreover, there is an upper-bound duration (8 weeks in this study) which is sufficiently long to suppress the attack rate and peak incidence to a nearminimal level, further extension of closure beyond this upper bound may be a waste of society resources. It is therefore recommended to evaluate the appropriate timing of school closure beforehand, especially in cost-cautious situation.

Enforcing a social distancing policy always associates with considerable cost, on both economic and social aspects. Take school closure as an example, its major cost comes from absenteeism of working parents who have to stay home to take care of their children. Besides, there are also problems about social justice, ethical issues etc. as the social consequences of school closure [10]. Policy makers always need to evaluate such social and economic costs together with the epidemic measurements when planning for social distancing interventions. If cost is put into the consideration, any extra reduction in attack rate or peak incidence due to proper timing would be favorable as no direct cost is incurred when varying the thresholds; meanwhile, any enhanced effort with prolonged duration should be deliberated because a substantial increase of cost might be resulted. Besides costs, there are other practical issues such as implementing all-school closure at a threshold as low as 0.02% may be a challenging decision for the policy makers to make, so it is with the case when closure is to be implemented at a high threshold of 10%. As huge cost is at stake, adequate justifications and evaluations are necessary before decision making.

The evaluation of intervention scenarios in this study is based on Singapore’s social structure. The results may vary: 1) when the social structure is dramatically different from the one studied in this paper as heterogeneity of social structure plays an important role in the disease transmission and therefore affecting the outcomes of mitigation planning strategies as well; 2) when the epidemic setting is dramatically different from the ones in this study. For example, a new influenza virus strain may have some unexpected new features in transmission rates, rates of asymptomatic infection, age distribution of infection and baseline immunity levels, etc. Though our study in Section III.D implies that many conclusions may still hold in different scenarios, the effectiveness of school closure could be quite different and the best timing needs to be carefully re-calculated accordingly. In addition, we used the percentage of symptomatic cases in the overall population as the trigger threshold in this paper. In real-life implementations, the number of symptomatic cases is often not accessible directly but has to be estimated based on the number of reported cases and the reporting rate. The unavoidable errors in estimation may also affect the effectiveness of intervention.

Besides the caveats mentioned above, social behaviors can drastically change during the period of high influenza incidences. Such changes obviously affect the disease propagation patterns and consequently affect the effectiveness of various intervention strategies including school closure as well. For example, parents staying at home can help strengthen the school closure distancing and at the same time, lowering the contacts at workplaces as well. On the other hand, some social gathering activities [25] may easily weaken the effectiveness of school closure, especially when school closure happens at early-stage of outbreak and people are yet not taking it very seriously. More comprehensive studies on such human behavior factors will be conducted in our future work, e.g., by relevant social survey, data collection and careful comparisons with historical epidemic data.

In this paper, we focus on studying the impacts of temporal factors on effectiveness of school closure. Whether school closure or any other intervention policy should be implemented in real life however also heavily depends on its associated costs, which requires careful and sophisticated measures. In-depth studies on costs and cost-effectiveness of intervention policies are also of our future research interest.

V. Conclusion

By conducting extensive simulations on an individual-based social network model, we studied the impacts of temporal factors on the effectiveness of school closure. Simulation results suggested that the trigger threshold and duration of school closure can both significantly affect the mitigation effectiveness, and proper timing is more important for school closure with a shorter duration. Such results provide useful insights for policy makers to make better decisions in influenza preparedness planning. The study also demonstrates the encouraging potential of a sophisticated individual-based simulation model in evaluating intervention policies in specific situations with specific constraints.

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