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An Agent-Based Simulation Model of Epidemic Spread in a Residential School for Children with Disabilities

RESEARCH

JESSICA DIMKA

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ABSTRACT

People with disabilities, especially those living in institutions, are at higher risk during pandemics, while schools also play important roles in disease spread. Yet, less attention is paid to the intersection of risk factors at residential schools for children with disabilities. Better understanding of spatial and behavioral factors that contribute to epidemics in such schools is needed for effective public health plans and responses, especially for pandemics where vaccines may be initially unavailable. An agent-based model of a school for deaf children was developed from Norwegian archival sources and 1918 influenza pandemic data to test impacts of non-pharmaceutical interventions. Results show differences in the timing and pattern of spread based on whether the first case is a student or staff member, while epidemics are smaller with more student bedrooms or a hospital ward. Implications for COVID-19 and future pandemics, including the need to combine different infection control measures, are discussed.

CORRESPONDING AUTHOR:

Jessica Dimka

Oslo Metropolitan University, NO

jessicad@oslomet.no

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In conclusion, I discuss the relevance of this work for COVID-19 and future pandemics, such as implications for staffing of such institutions and the development of improved pandemic preparedness plans.

METHODS

MODEL DESCRIPTION

As noted above, agent-based models are used to investigate system- or population-level outcomes produced by individual-level actions and interactions. The complex data requirements and the lengthy process of model design and analysis make these models less useful for rapid public health responses but ideal for explaining and understanding processes over time and space. The three main components of an agent-based model are agents (defined here as entities with heterogeneous attributes and behaviors; agents often represent people but could also correspond to smaller or greater scales, such as households), a world or environment, and rules of behavior that determine whether and how agents interact with each other and the world (e.g., Railsback & Grimm 2012). Agent-based epidemic models are typically used to explore the dynamic processes that contribute to disease spread, and they are particularly useful for research questions that involve small and/or isolated populations where individual variation and random factors likely play important roles in health outcomes. Emergent phenomena resulting from simplified behaviors and rules for transmission of disease between agents may include, for example, overall epidemic size and timing, spatial clustering of cases, or disparities between population subgroups.

The model described here draws on data on the Norwegian school system at the time of the 1918 influenza pandemic, obtained primarily from the National Archives of Norway, as well as system-level reports available online at Statistics Norway (https://www.ssb.no/). Permission to access restricted material was granted by the Director General of the National Archives via correspondence in September 2019. The archives contained annual and five-year reports for several schools, which provided details such as the demographics of the student population and information about curricula, staff, and health conditions. According to the 1918 system-level report, there were nine schools for children with disabilities, with an average of 39 boys, 27 girls, and 13 teachers (Kirke- og Undervisningsdepartementet 1923). Of the schools with available annual reports for 1918, the one with a distribution closest to this average was Holmestrand School for the Deaf (Holmestrand School for the Deaf 1920). This institution is therefore the primary inspiration for the modeled school, while additional insights are drawn from other archival sources.

The model, constructed in NetLogo 6.2.0 (Wilensky 1999), is described briefly below; more details and the full code are available online (Dimka 2022). The model environment (Figure 1)

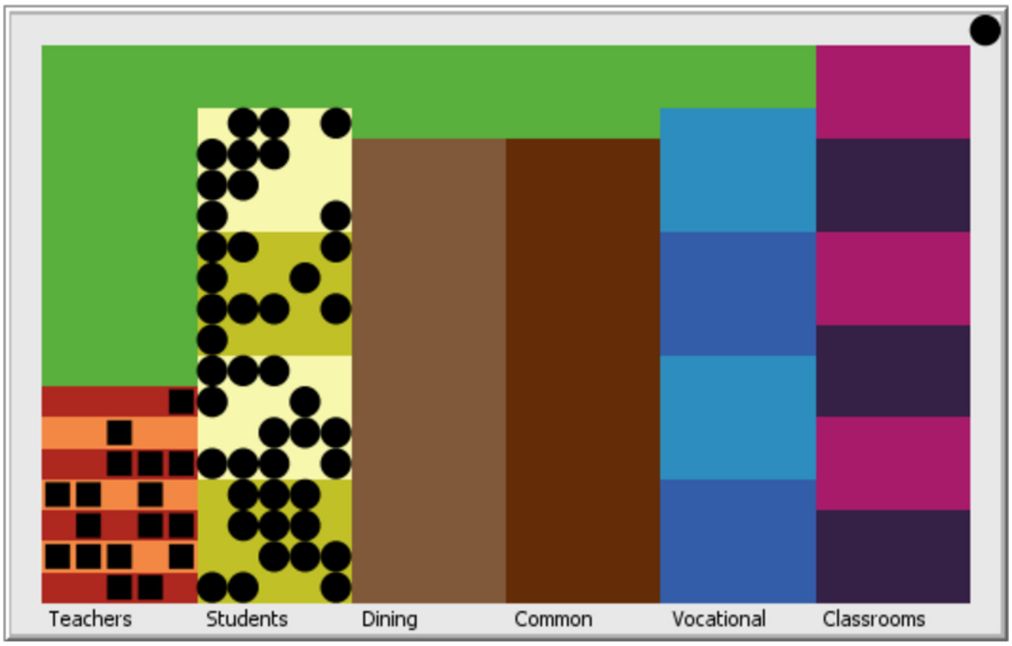

Figure 1 Visualization of the model at initialization.

consists of bedrooms, classrooms, a dining room, common room, and an outdoor area. Each time step (tick) of the model represents one hour, and a simulation runs for 800 ticks to allow sufficient time for epidemics to end. A default simulation begins on a Monday morning at 12 AM.

The 1918 Holmestrand population included 24 boys, 21 girls, the principal, six academic teachers, five vocational teachers, two gym/physical education teachers, and three boarding school staff members (n = 62). In the model, students are approximately evenly distributed into one class per grade level (1–6) and are divided into four dormitories by sex and younger and older grades. Several students stayed with nearby family or were boarded in local homes, so the remaining girl is classified as one such student. Staff share bedrooms with 0–3 others and are assigned an occupation (principal, teacher, etc.), class subject, and years of experience at the school.

Four major processes occur each tick. First, each agent updates its disease status. All but one agent is initially susceptible; the first case is randomly selected among the staff based on observations in records that disease was likely introduced to institutions by staff. This agent enters the exposed category at 6 AM, that is, tick 7. Others become exposed as a result of transmission during the simulation. Each tick, any agents in the exposed category will change to infectious if they have reached the end of the latent period (currently a constant value of one day). Agents who are already infectious when they begin this method have a constant chance of dying each tick. A random number between 0 and 1.0 is compared to the mortality probability parameter to determine whether death occurs. A surviving infectious agent then might recover, if it has reached the end of the infectious period. Recovered agents never become susceptible again.

Second, agents might move to a new social space depending on the day and time period. A random, unoccupied cell in the desired destination is selected. Only one agent is able to occupy any cell, but room dimensions generally allow all agents to be in their desired space. The bedrooms and classrooms can be relatively crowded, however, as suggested by photographs. Activity schedules are informed by school records, with several simplifying modifications; Table 1 provides an abridged list of what behaviors agents do when and where for Monday-Saturday. On Sundays, the schedules until breakfast and from dinner remain the same. From 9:00–11:00, all agents, except the external student who is absent the entire day, go to the common room, then to their bedrooms until 12:00. Except for lunch, students are split between the common room and external space all other periods. During each of these ticks, two staff members supervise each location. The caretaker always serves as one of the outside supervisors, while the next available adult besides the principal is the second supervisor. The next two adults are the common room supervisors for the tick, and all other adults go to their bedrooms. It should

Table 1 Abridged Schedule Monday–Saturday.

TIME BLOCK	ACTIVITY SUMMARY
Early Morning	• Staff wake at 6. • Students wake, housekeeper and housemother supervise younger student bedrooms at 7. • Breakfast at 8.
Morning	• External student arrives. • Students and academic teachers move once per hour within assigned classrooms. • Principal and vocational teachers remain in bedrooms. • Housemother and housekeeper may work together or in own rooms. • Caretaker in external space.
Afternoon	• Lunch at 1300. • Student free time at 1400: small chance of going outside, otherwise common room. All students to common room at 1500. • Vocational classes 1600–1800: subject chosen with some probability based on sex and space availability. Vocational teachers move within assigned classrooms 1500-1800. • Principal supervises common room at 1500. • Housemother and housekeeper supervise common room 1400–1600. • Caretaker in external space. • At 1800, boys and girls have gym or communication class on alternating days. These classes are held in restricted portions of the dining room and common room. • When not teaching or supervising, staff move to bedrooms.
Evening	• At 1900, external student leaves; all other agents eat dinner. • All agents to bedrooms at 2000; housemother and housekeeper supervise younger student bedrooms. • All staff to common room at 2100, then bedrooms at 2200.

be noted that student social and leisure behaviors outside of class, as well as staff schedules throughout the week, are less documented in the annual report and so are more speculative. Further, there is no attempt to model more specific friendships or interpersonal interactions based on, for example, gender or age, due to a lack of information on such relationships as well as for simplification purposes. However, the location of an agent within different social spaces is randomly selected each tick it moves to or within the space, allowing for varied interactions between agents at different times.

Third, disease transmission may occur between susceptible-infectious pairs of agents who come into contact with each other through shared behaviors (e.g., students in the same class). Susceptible agents check if they have any infectious neighbors in cells to the north, south, east, and west within the same social space. If so and if a random value between 0 and 1.0 is less than the transmission probability parameter, the susceptible agent changes its disease status to exposed. A similar process takes place for infectious agents who look for susceptible neighbors. As indicated by this process and the method updating disease status, the transmission and progression of influenza is determined by epidemiological factors rather than presence of symptoms.

Fourth, substitutes for teaching or supervision duties are identified for staff who died during the current tick. Upon the death of a teacher, the principal is assigned to substitute, then the housemother if he is unavailable. If a third teacher dies, or earlier, if the principal and/or housemother is unavailable, classes are canceled, and students stay in their bedrooms during class periods for the rest of the simulation. If the principal dies, the most senior surviving teacher assumes those supervision duties but does not change its regular behavior otherwise. If the housemother or housekeeper dies, a female teacher assumes supervision duties. Similarly, if the caretaker dies, a male teacher moves outside when that agent is supposed to supervise students. In this default model, there are no other individual- or institutional-level behavior changes to reflect illness or in response to deaths.

DISEASE PARAMETERS

The durations of the latent and infectious periods, one and three days respectively, were chosen based on an assessment of literature (e.g., Cori et al. 2012; Mills, Robins, & Lipsitch 2004). School reports lacked quantitative information about the level of illness but indicated the attack rates were substantial. Holmestrand reported that 'all children were affected by the flu' (Holmestrand School for the Deaf 1920). Similarly, the 1919 annual report for a school in Pennsylvania for children with intellectual disabilities noted that more than 80% of the population had been infected (Chamberlain 2020). Therefore, the transmission parameter was calibrated through preliminary simulations to achieve a target attack rate of approximately 80%, giving a per-contact transmission probability of 0.014.

The Holmestrand report noted that two children (~4.4%) died from the flu in 1918, while no staff deaths were reported (Holmestrand School for the Deaf 1920). Further, mortality was also estimated for records extracted from the Demographic Data Base at Umeå University for individuals residing in nine Swedish parishes between 1918 and 1920 that included causes of death and disabilities marked by parish pastors (CEDAR 2020). Of 58 children aged 5–15 with recorded disabilities, there were two deaths attributed to influenza-related causes (~3.4%). Therefore, the estimated mortality rate for disabled children during the 1918 pandemic is 3–4%. The limited data from schools suggest there were few deaths among the presumed non-disabled staff. However, these sample sizes are small, and staff health was generally not a focus of the narrative reports. Rough estimates from the Umeå database suggest that, out of 18039 individuals aged 15–65 with no recorded disabilities, there were 454 influenza-related deaths (~2.5%). For simplification purposes and to test whether differences in student and staff outcomes can be explained by social and institutional factors alone, a single mortality rate of 3% is used for the default model. This rate was used to calculate a mortality probability of 0.00053 per tick of the infectious period (details in Dimka 2022).

EXPLORATORY SIMULATIONS

Results presented here have two aims: first, baseline simulations were run to determine whether the model produces reasonable and expected outcomes. Second, three potential mechanisms to explain patterns of epidemic spread within institutions and identify pathways for interventions are considered. First, simulations where the first case is a residential student (for example, due to exposure from a visitor or a trip outside the school) are compared to those introduced by a staff member. Second, the number of students who shared a bedroom may have varied based on school size, financial resources, or student age. In the default model, there are four rooms of 10–12 students each, and this is compared to an alternative scenario allowing eight bedrooms of 5–6 students each. From an epidemiological perspective, fewer students sharing promotes more social distancing. Finally, a hospital ward is added to the model, allowing for the isolation of at least some infectious agents away from the rest of the population. If an infectious student does not die or recover during a tick of the infectious period, it has a chance of being removed from its typical activity and placed in the ward; staff members are not hospitalized in this scenario. Although some literature has reported estimated risks or rates of hospitalization for preschool and school-aged children in recent pandemics and seasonal influenza (e.g., Encinosa, Figueroa, & Elias 2022; Hauge et al. 2020), plausible rates for already institutionalized children with medical risk conditions are more difficult to identify. Rather, using a similar strategy as with the mortality probability, a per-tick hospitalization probability was calculated. Sensitivity analyses varying this probability were run to achieve a target hospitalization of approximately 5–25% of all children in increments of 5%.

Repetition analyses indicated that 500 simulations are sufficient to capture general model behavior relative to stochastic "noise" (see Dimka 2022). Thus, for all scenarios, 500 simulations were run, with analyses conducted on epidemic runs only, defined as >6 agents (10%) ever infected. The outcomes reported here include average size and timing measures. The final size (% ever infected) is presented separately for the student, staff, and total populations, while mortality (% dead) and peak size (maximum % infectious during a simulation) are calculated for the total population. The proportion of children who are ever hospitalized is also reported. The peak day is calculated as the average of the first and last tick the peak size was recorded, divided by 24 (again, each tick represents 1 hour), while the last day is the last tick any agent was infectious, divided by 24. Finally, the day to epidemic threshold is the first tick where the number of susceptible agents dropped below 56, based on the definition of an epidemic above, divided by 24.

RESULTS

As expected, baseline simulations produce epidemics where, on average, approximately 80% of the population is infected and 3% dies (Table 2). This impact is not equally distributed, however. On average, 86.2% of the students are infected compared to 62.6% of the staff ($t = 16.94$, $p < 0.00$), while 3.4% of the students and 2.6% of the staff die ($t = 2.73$, $p < 0.01$). Epidemics reach the threshold about one week after the start of the simulation, peak one week later, and end ten days after that.

Relative to the baseline, the scenario where a student is the first case produces substantially more epidemics, which reach the threshold, peak, and end significantly earlier by about one, two, and one days, respectively (Table 2). Significantly fewer teachers become infected, but there are no differences in the proportion of the student or total population affected or the peak size. The shapes of the average epidemic curves for the subgroups also vary depending on the first case (Figure 2). In the baseline scenario, the staff curve appears bimodal, with the proportion of infectious staff reaching a quick early peak and then another one after the student peak. Meanwhile, the student curve begins to rise somewhat, although not dramatically, later into a single peak. When a student is the first case, the staff curve has a single, more sustained peak. In both scenarios, the overall curve mirrors that of the much larger student population, obscuring the differences between the subgroups.

When there are more student bedrooms, epidemics have significantly smaller peak and final sizes, with the student population clearly benefiting more than the staff (Table 2). There are no or marginal differences in timing between this scenario and the baseline model. Similarly, the introduction of a hospital or isolation ward, using a default hospitalization parameter of 0.003 (15% target), also significantly reduces the final and peak sizes of epidemics but does not meaningfully affect the timing of the peak or duration of the outbreak compared to the

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Table 2 Average epidemic outcomes (±1 standard deviation) for modeled scenarios.

t-test vs. baseline: * $p < .1$, ** $p < .05$.

SCENARIO	NUMBER OF EPIDEMICS (%)	FINAL SIZE -TOTAL (%)	FINAL SIZE – STAFF (%)	FINAL SIZE – STUDENTS (%)	MORTALITY (%)	PEAK SIZE (%)	DAYS TO EPIDEMIC THRESHOLD	PEAK DAY	LAST DAY
Baseline	234 (47)	79.7 ± 13.0	62.6 ± 15.9	86.2 ± 14.2	3.1 ± 2.2	29.0 ± 7.4	6.4 ± 2.1	14.0 ± 3.7	24.3 ± 4.1
Student First Case	400 (80)	78.7 ± 12.8	58.0 ± 18.9**	86.5 ± 13.4	3.0 ± 2.2	29.2 ± 7.4	5.2 ± 1.7**	12.2 ± 3.4**	23.0 ± 4.2**
More Bedrooms	227 (45)	74.7 ± 15.6**	63.1 ± 17.5	79.1 ± 17.2**	2.8 ± 1.8**	25.1 ± 7.3**	6.2 ± 2.2	14.3 ± 3.9	25.0 ± 4.3*
Hospital (~15%)	243 (49)	72.9 ± 16.9**	57.6 ± 18.5**	78.7 ± 18.9**	2.6 ± 2.1**	25.7 ± 7.9**	6.0 ± 1.9**	13.8 ± 3.8	24.2 ± 4.5

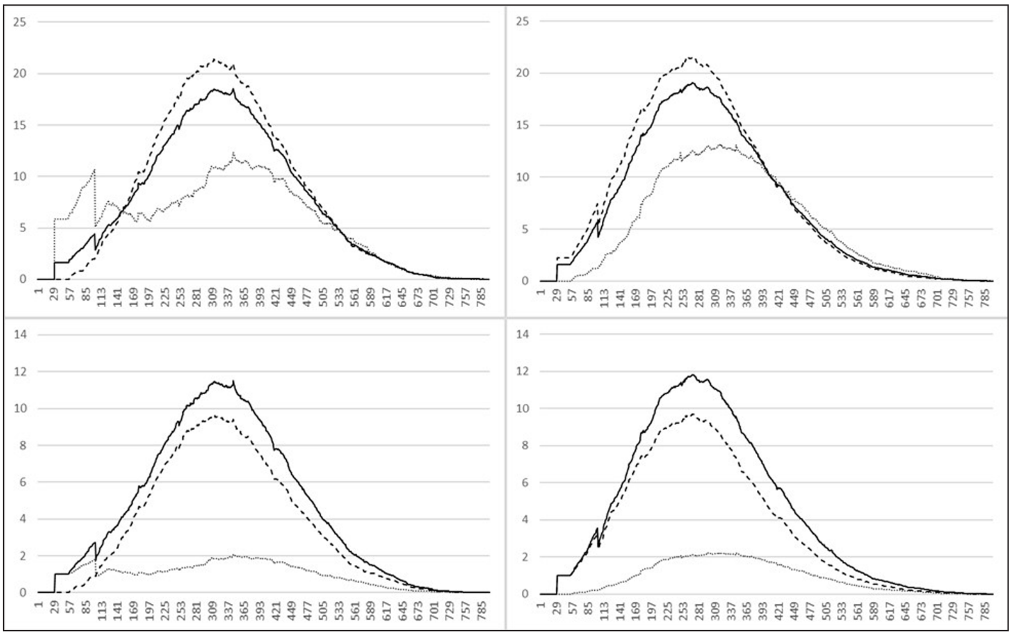

Figure 2 Average epidemic curves showing infectious agents over time (in increments of one tick) as the percentage of each subgroup (top) and number of cases (bottom), when the first case is a staff member (left) or residential student (right). Each graph includes curves for the overall population (solid line), staff (dotted line) and students (dashed line).

baseline. Although the time to epidemic threshold is significantly shorter with hospitalization, this difference is <1 day.

Varying the hospitalization probability shows that an increased chance of hospitalization also reduces the final and peak proportions of the population affected, with no or marginal effects on the timing of epidemics (Table 3). Post hoc pairwise t-tests indicate that the size differences are largely driven by lower hospitalization probabilities, while there are no significant differences in final and peak sizes produced by the three largest values (results not shown). While the actual proportion of children hospitalized is larger than the target for lower values of the probability, it is noticeably lower than expected with larger values. The difference between target and actual hospitalization at 0.005 (25% target) is 2.3%, compared to 1.1% or smaller differences for other values. Although rounding of the parameter estimates may contribute to variation from the target, the clear trend suggests that the reduction in the at-risk population (i.e., infectious students) may better explain this result.

DISCUSSION

In addition to the intentional final size and mortality outcomes, the baseline model produces emergent timing outcomes – a peak at about two weeks and termination at about three weeks – that are consistent with observations (Table 2). Norwegian school records noted that the majority of cases occurred within one or less than two months, while Adams (2020) documented that half of the student population at the Haskell Institute, a federal Indian residential school in Kansas, had severe cases within two weeks during the first wave of the 1918 pandemic, while the second wave lasted about one month.

Research on psychiatric institutions and tuberculosis sanatoria in Norway demonstrate a crossover where more staff fell ill but there was a higher case fatality rate for the patients (Dimka & Mamelund 2020; Mamelund & Dimka 2019). Such a crossover would not be possible with the current model processes. Further, these outcomes may reflect underlying susceptibility and/or social and environmental factors, and so would not necessarily be expected within schools. Indeed, school reports suggest that there were more student cases as well as more deaths. The model does show that significantly different outcomes between students and staff can occur from social behaviors alone, even when all agents share constant transmission and mortality probabilities (Table 2, Figure 2). However, the practical implications of statistically significant but absolutely small differences must be considered, as the discussion below demonstrates. This concern is also relevant given the range of variation around many of the averages, likely due in part to the small sample size.

Historically and today, most infectious diseases are likely introduced to institutions via staff, especially when there is restricted visitation. Records from psychiatric institutions noted that

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Table 3 Average epidemic outcomes (±1 standard deviation) varying the probability of hospitalization.

* p <.1, ** p <.05.

HOSPITALIZATION PROBABILITY (TARGET %)	NUMBER OF EPIDEMICS (%)	FINAL SIZE -TOTAL (%)	FINAL SIZE – STAFF (%)	FINAL SIZE – STUDENTS (%)	MORTALITY (%)	CHILDREN HOSPITALIZED (%)	PEAK SIZE (%)	DAYS TO EPIDEMIC THRESHOLD	PEAK DAY	LAST DAY
0.001 (5)	243 (49)	78.6 ± 11.7	61.3 ± 17.6	85.2 ± 12.7	3.1 ± 2.2	6.1 ± 3.7	28.2 ± 7.0	6.3 ± 2.0	14.2 ± 3.7	24.6 ± 4.2
0.002 (10)	233 (47)	74.9 ± 16.7	58.7 ± 18.1	81.1 ± 18.7	2.5 ± 1.9	10.8 ± 4.7	27.1 ± 8.0	6.4 ± 2.2	13.5 ± 3.7	24.1 ± 4.5
0.003 (15)	243 (49)	72.9 ± 16.9	57.6 ± 18.5	78.7 ± 18.9	2.6 ± 2.1	14.8 ± 5.6	25.7 ± 7.9	6.0 ± 1.9	13.8 ± 3.8	24.2 ± 4.5
0.004 (20)	231 (46)	71.6 ± 18.4	56.3 ± 20.5	77.4 ± 20.1	2.8 ± 2.2	18.9 ± 6.7	24.8 ± 7.5	6.4 ± 2.2	14.1 ± 4.0	24.2 ± 4.9
0.005 (25)	242 (48)	70.5 ± 19.3	56.5 ± 19.1	75.7 ± 21.8	2.7 ± 2.1	22.7 ± 7.9	24.7 ± 8.4	6.0 ± 2.1	13.3 ± 4.1	23.6 ± 4.8
ANOVA ($F_{4, 1187}$)		8.9**	2.8**	9.4**	2.9**	293.3**	9.2**	2.1*	2.2*	1.3

cases spread earlier among staff before entering the patient population (Dimka & Mamelund 2020). Simulation results suggest that this pattern would be expected with a staff member first case, but not with a residential student first case. As Figure 2 shows, the absolute differences in initial spread between the two subgroups are not striking, but these differences may be more noticeable in institutions with stricter segregation or larger populations. Further, even the slight delay (in these results, just over one day) before the epidemic threshold is reached when a staff member is the first case may be actionable with careful surveillance and rapid response, potentially preventing an epidemic from occurring in the first place.

Simulations also show significant differences in epidemic size when fewer residents share bedrooms, consistent with findings in other research (Brown et al. 2021). Comparisons show that, as would be expected since there are fewer possibilities for transmission between students, the practice benefits the students while there is no effect for the staff (Table 2). Large dormitories may have been common among students historically, whereas newer schools or care homes may allow single rooms or sharing among only a few individuals. In the modeled scenario, only approximately three more students, on average, escaped infection, but the benefit could be even more substantial with more rooms or less sharing. Further investigation is needed on the variation in housing structure among different types of institutions, including whether staff are also residents.

Hospital or isolation wards, which also reduce epidemic size in the model, may be or have been more common in larger institutions and/or in more isolated institutions that do not have access to surrounding health care resources. Comparison of the extra bedrooms and hospital scenarios show significant differences for only the average last day and the proportion of staff affected (results not shown); as seen in Table 2, these differences are not practically meaningful however (i.e., less than one day and 5.5%, or approximately one case). The similarities between the scenarios reflect the fact that they both play roles in reducing contacts and thus breaking links in chains of transmission. Further, the lack of significant differences between larger probabilities of hospitalization suggests there may be a threshold after which additional benefits from this isolation are negligible, without other health-related behavior change. In the current scenario, hospitalization does not influence other disease parameters, i.e., agents still have the same infectious period durations and mortality probabilities. Although there were no effective antivirals or vaccines at the time of the 1918 pandemic, nursing care was important for patient outcomes (Mamelund 2011). Therefore, additional benefits would be expected if the model adjusted for this care, including fewer deaths and the earlier reintroduction of recovered, non-susceptible individuals who could serve as ‘buffers’ in the social spaces (essentially, contributing to herd immunity).

LIMITATIONS AND FUTURE WORK

Models are simplified representations of a more complex reality (Sattenspiel 2003). Despite potential criticisms of being too simple or unrealistic (Waldherr & Wijermans 2013), it is good practice to construct models in increasingly complex stages in order to test assumptions, ensure the model is working as intended, and more thoroughly understand the mechanisms behind emergent results rather than simply producing ‘black box’ processes and outcomes (e.g., Railsback & Grimm 2012; Sattenspiel 2003). In addition to limitations noted above, the current version of the model does not yet include differences in susceptibility to infection or death based on demographic characteristics or disability status. This exclusion was deliberate in order to focus on social, spatial, and behavioral factors relevant to non-pharmaceutical interventions. Another added value is that results may provide insights for other schools, such as residential schools for Indigenous students, which were also strongly impacted during the 1918 flu (Adams 2020). Nonetheless, biological mechanisms (e.g., immunosuppression or reduced respiratory function) also may explain disparities among people with disabilities (e.g., Bracchi-Ricard et al. 2016; Centers for Disease Control and Prevention 2012; Havers et al. 2014; Perez-Padilla et al. 2010). Future applications of the model will test varying parameter values to reflect disability status as well as age. Importantly, teachers in some schools for children with disabilities may have shared these conditions (such as deafness or blindness) and thus the associated potential risk.