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The Role of Subway Travel in an Influenza Epidemic: A New York City Simulation

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ABSTRACT *The interactions of people using public transportation in large metropolitan areas may help spread an influenza epidemic. An agent-based model computer simulation of New York City's (NYC's) five boroughs was developed that incorporated subway ridership into a Susceptible–Exposed–Infected–Recovered disease model framework. The model contains a total of 7,847,465 virtual people. Each person resides in one of the five boroughs of NYC and has a set of socio-demographic characteristics and daily behaviors that include age, sex, employment status, income, occupation, and household location and membership. The model simulates the interactions of subway riders with their workplaces, schools, households, and community activities. It was calibrated using historical data from the 1957–1958 influenza pandemics and from NYC travel surveys. The surveys were necessary to enable inclusion of subway riders into the model. The model results estimate that if influenza did occur in NYC with the characteristics of the 1957–1958 pandemic, 4% of transmissions would occur on the subway. This suggests that interventions targeted at subway riders would be relatively ineffective in containing the epidemic. A number of hypothetical examples demonstrate this feature. This information could prove useful to public health officials planning responses to epidemics.*

KEYWORDS *Computer simulation, Infectious disease transmission, Human influenza, Subway travel, Agent-based model, Pandemic*

INTRODUCTION

An important part of planning for an influenza epidemic is to understand how the epidemic spreads throughout a health care planning region. Most preparedness plans are designed to maintain "business as usual" and resort to high-impact interventions only when officials find substantial evidence of a high rate of disease spread. In a large metropolitan area, if infected patients use the public transportation (PT) facilities to maintain their normal daily routine, they will interact closely with

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other PT users, who in turn will interact with other uninfected people, including their colleagues and family members. In this paper, we investigate the possible effect that users of a specific mode of transportation—a large metropolitan subway system—may have on the spread of influenza. In particular, we investigate the role the New York City (NYC) subway system could play in spreading influenza throughout the five boroughs of NYC.

Among American cities, New York has the highest subway ridership populations. Consequently, we posit that PT interventions effective in NYC will be less effective in other US cities due to lower ridership rates. To address this issue, we developed an agent-based model (ABM) computer simulation of NYC's five boroughs that incorporates subway ridership into a Susceptible–Exposed–Infected–Recovered (SEIR) disease model framework. The model simulates the interactions of subway riders with their workplaces, schools, households, and community activities. It also examines the impact that a severe influenza epidemic would have on NYC and the potential effects of different hypothetical subway-related disease control measures. To support this assessment, the model explicitly stratifies subway riders as commuters, shoppers, and miscellaneous travelers. The model also compares interventions that target specific NYC subpopulations including subway riders.

MATERIALS AND METHODS

Model Structure and Synthetic Census-Based Population

Figure 1 illustrates the NYC five-borough region in our simulation. We used a method developed by Beckman et al.[1] to help extract the agent population from the US Census Bureau's Public Use Microdata files and Census aggregated data.[2] The model contains a total of 7,847,465 computer agents, or virtual people. Each person

FIGURE 1. The New York City five-borough region.

resides in one of the five boroughs and has a set of socio-demographic characteristics and daily behaviors that include age, sex, employment status, occupation, and household location and membership. Students and teachers are assigned to schools, and employed adults are given employment status and locations. All persons are given disease status.[3] A total of 2,005,024 people are under 18 years of age, and 848,590 are over 65.

The model also depicts the region's individual households, schools, and workplaces, with people assigned to each using the methods above and the following data sources.

- Public and private schools and school assignments came from the US Department of Education National Center for Education Statistics. A total of 2,073 public and private schools were included in the NYC region with a total of 1,467,884 students of school age (5–17) in attendance.
- Workplaces and workplace assignments were taken from US Census Standard Tabulation Product (STP64) commuting pattern data and ESRI Business Analyst (InfoUSA business data). The NYC region included 116,979 workplaces with 2,858,151 employees. The distribution of firm sizes included: 4,813 with over 100 employees, 7,372 with 50 to 99 employees, 5,987 with 20 to 49 employees, 20,045 with 10 to 19 employees, and 78,239 with <10 employees. Nearly 70% of these workers commute to work 5 to 7 days a week by subway, bus, by their own vehicles, or as part of a car pool, but a significant percentage (>16%) walk to work.[4]
- Commuting estimates for public transportation by mode of travel were taken from 2000 US Census data. Non-commuting patterns of travel were obtained from the following travel surveys:
  - New York Household Travel Patterns: A Comparison Analysis[4]
  - The 1997/1998 Regional travel/Household Interview Survey[5]
- Characteristics of subway riders were identified in an analysis of the 2006 Community NYC Health survey.[6] Each virtual person was assigned a probability of using the subway based on information regarding the characteristics.[7]

A detailed description of agent parameters is provided in the Electronic supplementary material (ESM) document that provides a fuller description of all aspects of the model.

Disease Parameters

At any given time, each person is in one of four mutually exclusive states: susceptible (S), exposed (E), infectious (I), or recovered (R). All people are initially susceptible (S) to disease until infectious individuals are introduced into the model. Contact with an infectious person has an assigned probability of disease transmission from the infectious person to the susceptible person, as listed in Table 1, derived from studies by Longini et al.,[8] Ferguson et al.,[9] Germann et al.,[10] Ferguson et al.,[11] and Halloran et al.[12] on the basis of the 1957–1958 Asian influenza pandemic. For example, as the second row in Table 1 indicates, an infectious child coming into contact with a susceptible adult in a shared household has a 30% probability of transmitting the virus to the adult per contact. By comparison, the fifth row of Table 1 indicates that an infected elementary school student who comes into contact with a susceptible student has a 4.35% probability of transmitting the virus per contact.

A newly infected person moves to the exposed (E) state for the duration of the disease's incubation period and then to the infectious state (I), in which the person may infect others.

TABLE 1 Model transmission parameter values

Contact group	Infected	Susceptible	Transmission probability[a]
Household	Adult	Adult	0.4
Household	Child	Adult	0.3
Household	Adult	Child	0.3
Household	Child	Child	0.6
Elementary school	Student	Student	0.0435
Middle school	Student	Student	0.0375
High school	Student	Student	0.0315
Workplace	Adult	Adult	0.0575
Hospital	HCW	HCW	0.0575
Hospital	HCW	Patient	0.01
Hospital	Patient	HCW	0.01
Community	All	All	0.0048

[a]Transmission estimates are obtained from Ferguson et al.[9], Halloran et al.[12], and Longini et al.[8]

Consistent with the results of the Models of Infectious Disease Agent Study (MIDAS) combined-model study, two-thirds of infectious patients exhibit symptoms.[8,12] After the infectious period, the person enters the recovered state (R) and remains immune to subsequent infections for the remainder of the simulation.

The simulations incorporated a set of assumptions that described movements and contact patterns of individual people within the five-borough population which are based on research done in other MIDAS network models.[12–15] People move back and forth from their households to designated workplaces for employed adults and to schools for school-aged children, where they interact with other people in close proximity based on endogenously estimated contact rates.

Also, people interact daily with family members in the same household. In schools and workplaces, students and workers contact a fixed mean number of people per day representing that person's classroom or office. Each person also has an additional random probability of interacting with other people within the same school or firm, but in different classrooms or offices. Workers in firms that have only one office repeatedly contact the same people each day. Every day, all people potentially interact with each other in the community, although with a fairly low probability of transmitting the virus. On weekends, students do not go to school, but their community interactions increase by 50%.[16]

Our base model also assumes that 20% of working adults work on weekends.[17] Our base model also assumes that 50% of sick students and workers, that is, agents in stage I, stay home with no community contacts unless they see a doctor, and 40% of patients with influenza symptoms visit a clinic or emergency department. These values have been used in previous studies, and the sensitivity of changes to these assumptions and their effect on simulated epidemics are examined in the ESM document that provides a fuller description of the model.[8, 10–12, 17–21]

Model Calibration

The model was calibrated using historical data from the 1957–1958 and 1968–1969 influenza pandemics. Our calibration targets were derived from the assertion defined by Ferguson et al. that postulates that 30% of all influenza transmissions occur within the household, 33% occur in the general community, and 37% occur in schools and workplaces.[9] These calibration targets apply to epidemics with a basic reproduction rate, R_0=1.4. It was also necessary to add a new subway-based parameter to the calibration process. The total number of subway riders and the proportion of those that commute are available from the NYC transportation department (see below under "Subway Ridership" discussion) and census data, respectively.[4,5] These parameters are treated as exogenous variables, but an endogenous parameter, the probability of being a subway rider, was incorporated into the calibration process.

Social Network Contact Rates We estimated social-network-specific contact rates and applied them in our SEIR simulation framework together with NYC household/demographic data to generate results to satisfy the calibration criteria. The usual social networks represented in the model were: households, schools, workplaces, and a general category of community interactions. Two new social networks were added: subway riders that commute to work and subway riders that are not commuting. The strategy was to generate influenza epidemics that characterize the behavior of the 1957–1958 pandemic in the NYC setting.

Our position also posits that subway ridership and its potential for spreading an epidemic is particularly relevant to NYC, where almost 30% of city dwellers ride the subway. Nearly eight out of ten New York State households without a vehicle are in NYC, and 36% of NYC commuters walk to work.[5]

However, despite evidence of people using public transport, subway ridership and subsequent influenza transmission during subway travel has not been described in the literature and has not been represented in other models.

Even though available data allow us to identify the agent population that always uses the subway, there is no obvious way to separate transmissions between commuters from transmissions in the workplace without knowing the relative exposures within the separate social networks. Thus, to estimate transmission on the subway, we added the two social networks identified above that have not been included in other disease transmission models: commuters that ride the subway as their principal mode of transportation to work (30.2% of NYC commuters)[22] and persons who ride the subway as part of their day-to-day social interactions within the general community, i.e., outside of workplaces and schools.

Calibration Details A revised process for calibrating the modified model to the criteria established in Ferguson et al.[9] was developed. We assigned subway riders identified as commuters to the workplace social network, and shoppers and other non-commuters to the community social network. Reliable estimates of subway ridership exist; however, the relative contact exposures of subway riders waiting at the station and riding the train are not available.

Our approach factors into the estimation process the relative contact exposure rates for each of six endogenous variables (one each for workplaces, schools, and community; two for subways; and one for households) that compromise the six broad social network groups portrayed in the model (households, schools, workplaces, subway riders—commuters, subway riders—non-commuters, and communities). The strategy is to estimate the six estimated contact rates that generate an epidemic that satisfies the 30–70 (household transmission versus other sites) rule calibration criteria.[9] The estimation process used the downhill simplex method of Nelder and Mead[23] to fit the source of infection estimates to the 1957–1958 flu pandemic-based calibration criteria. The estimation approach estimates the relative exposures realized by each of the six social network categories. The exposures are adjusted by transmission probabilities (from Longini et al.)[8] that account for the different interaction properties inherent to the different social networks. For example, the adult-to-adult transmission probability in households is substantially higher than the adult-to-adult transmission probabilities between shoppers. This in part reflects the closer quarters in a household than in a shopping mall.

Additional Model Assumptions

The other (non-contact) disease parameters and assumptions are consistent with the MIDAS studies.[9–15] For example, we assume that 50% of sick students and workers stay at home and do not interact with anyone outside of the household. Our workplace absentee rate is also consistent with those models. However, we use a school absentee rate that is generally lower than other models (Ferguson et al. used a 90% absentee rate).[1] We also included the following assumptions from our base model: 50% of sick students and workers stay home with no community contacts unless they see a health care worker (HCW); 20% of working adults work on weekends; and student/community and adult/community contacts increase by 50% on weekends.

The rationale for using the above defined calibration method is based on our goal of objectively discriminating between infections that occur in the workplace, those that occur commuting to work, those that occur in the community (shopping, etc.), and those that occur while traveling to community activities. Census data provide the number of commuters and where they reside and work. The NYC health survey identified subway riders from the non-commuting population and where they reside.

Subway Ridership A key component for calibrating the model was to obtain reliable subway ridership information. Table 2 shows an estimate of total NYC subway ridership trips for 2008 by total annual ridership, including daily ridership for weekdays, Saturdays, and Sundays. The ridership information was obtained from Metropolitan Transportation Authority sources for NYC (see http://www.mta.info/nyct/facts/ridership/index.htm). The information is identified as turnstile entry, and for our study, we assumed that two turnstile entries define a single outbound and inbound trip.

To further refine the calibration, we were specifically interested in determining the distribution of commuters and non-commuters as subway riders. The estimate of subway daily riders shown in Table 3 is based on the 2000 Census data. The estimate of 2,398,082 subway trips per weekday assumes that each commute

TABLE 2 Total subway ridership figures for 2008

Category	Annual	Average weekday	Average Saturday	Average Sunday
Trips	1,579,866,600	5,086,833	2,928,247	2,283,601
Riders[a]	789,933,300	2,543,417	1,464,124	1,141,801

Source: http://www.mta.info/nyct/facts/ridership/index.htm
[a]Assumes that each rider turns the turnstile twice for a single outbound and inbound trip

TABLE 3 Subway daily riders assumptions

Category	Weekday	Saturday	Sunday
Commute trips	2,398,082	479,614	0
Commuters	1,199,041	239,807	0
Other trips	2,688,751	1,224,317	2,283,601
Non-commuters	1,344,376	1,151,359	1,141,800
Total trips[a]	5,086,833	2,928,247	2,283,601
Total riders	2,543,147	1,464,124	1,141,800

[a]http://www.mta.info/nyct/facts/ridership/index.htm

involves a trip to and from the workplace. Saturday commuters were assumed to be 20% of the weekday estimate.

The residual (non-commuter) trips were estimated as the difference between 5,086,833 total trips and the 2,398,082 commute trips. The difference (2,688,751) is the non-commute subway trips per weekday. This shows that a slight minority (47.1%) of all subway transit trips are for commuting purposes on weekdays. This is consistent with census data.[22]

To summarize, to incorporate subway rider social network into our NYC model, we did the following:

- Identified commuters who used the subway to travel to work from the 2000 Census data;
- Estimated non-commuting trips by subway riders to shop, socialize, and conduct daily activities from total ridership data with commuters removed from the total count;
- Generated trips of a non-commuting nature at random for each NYC dweller over the age of 5 with the probability of a person riding the subway depending on age, day of the week, and proximity to a subway station;
- Simulated commuter and non-commuter subway riders interacting with *X* other subway riders traveling in the same physical space, where *X* is defined as the number of contacts made between the index case and the proportion of riders sharing the air space on a subway train and at the station per day (Table 4);

TABLE 4 Estimated (derived) person-to-person contact values (contacts per day)

Place	Participant	Mean contacts per day	Social network
Within school[a]	Student	14.98	School
Per firm[a]	Worker	1.84	Workplace
Subway[a]	Worker (commuter)	33.88	Subway
Subway[a]	Non-worker	6.75	Subway
Community[a]	Non-student	34.80	Community
Household[a]	All	.922[b]	Household
Classroom[c]	Student	29.96	School
Community weekday non-school[c]	Student	7.50	Community
Community weekend non-school[c]	Student	11.24	Community
Per office[c]	Worker	3.68	Workplace

[a]Estimated
[b]Daily contact probability per person
[c]Based on estimates in rows 1–6

- Treated the value of X as an endogenous variable and used it to reproduce the 1957–1958 epidemic according to the validation criteria;
- Applied daily contact parameters to other social networks and also (simultaneously) treated them as endogenous variables to fit the calibration criteria (Table 4);
- Fixed the estimated contact rates to generate the baseline (no intervention) runs result (as shown in "Results"); and
- Separated interactions among the subway riders for commute and non-commute purposes from interactions in the workplace.

Using this model, we assessed community activities and interventions affecting subway transmission patterns. See the ESM for a fuller description of the calculation process.

Epidemic Simulations

We ran the model and generated 20 calibrated epidemics using 20 distinct random number sequences, each seeded with ten single-infected adults. The variance in the epidemic process is small for fixed-contact estimates. The tables of results below present the mean value estimates only.

To examine the spectrum of potential influenza transmissions, we simulated the effects of various prior immunity levels, the effects of different interventions on subway transmissions and R_0, or the number of secondary cases that a typical infected person will produce in a completely susceptible population.

The ABM was programmed in C++ and is naturally parallel regarding statistical realizations. Simulations were performed on the RTI Opteron-based Linux cluster. Each simulation run took an average of 5 minutes and operated over 32 computational cores.

RESULTS

Calibration Results

Table 4 lists the estimated number of contacts per day per social network category. These parameters define the baseline model.

The distribution of infection by the source of infection for the calibrated or reconstructed 1957–1958 pandemic model is presented in Table 5. This table identifies the social network categories (place), the size of the social networks (population), the number of infections estimated by the model (infections), the percentage of the total infections (%), and the ratio of infections per unit of population (at risk).

TABLE 5 Baseline source of infection results

Place	Population	Infections	% Infections	At risk (per 1,000)
Households	7,847,445	777,161	30.0	99.03
School	1,467,884	643,152	24.5	438.15
Workplace	2,858,151	226,075	8.9	79.10
Subway commute	1,199,041	94,394	3.6	78.73
Subway other	1,344,376	19,637	.8	14.61
Other (community)	7,847,445	837,956	32.2	106.78
Total	7,847,445	2,601,375	100.0	331.49

Table 5 indicates that 4.4% (114,031) of the 2.6 million cumulative infections that compromise the simulated epidemic occurred on the subway with the distribution between commuters (3.6%) and non-commuters (<1%) shown. This table also indicates that with a risk factor of 78.73 per 1,000 for infection, subway commuting poses a risk comparable to working. However, occasional use of the subway, i.e., riders that are not commuters, posses the lowest risk of all categories. Students attending school have the greatest risk.

Prior Immunity Impacts

The baseline run was intended to simulate the 1957–1958 type (no immunity) of epidemic in NYC if it occurred today. However, a more relevant scenario would be to simulate an epidemic that assumed the form of the H1N1 epidemic of 2009. To simulate the H1N1 epidemic, we investigated obtaining estimates of prior immunity to H1N1 and adding them to the baseline model. We looked to recent studies concerning the H1N1 epidemic of 2009, which was a global outbreak of a new strain of H1N1 influenza virus. First described in April 2009, the virus appeared when a previous triple assortment of bird, pig, and human flu viruses combined with a Eurasian pig flu virus.[24] Unlike most strains of influenza, H1N1 does not disproportionately infect adults older than 60; this was an unusual and characteristic feature of the H1N1 epidemic and indicated that prior immunity was a major difference between the epidemics of 1957–1958 and H1N1. To estimate this influence, Miller et al.[25] conducted a cross-sectional serological survey on English patients, based on 1,403 serum samples taken in 2008 before the first wave of H1N1 and 1,954 serum samples taken in August and September 2009, after the first wave.

We applied the estimates of prior immunity from this study and added them to our baseline NYC model. Table 6 compares the infection attack rates of the baseline (no prior immunity—the 1957–1958 reconstruction) and the H1N1 of 2009 reconstruction (with prior immunity) epidemics. Overall, applying prior immunity rates dropped the attack rate (AR) about 10 percentage points from 33% to 22.4%. While an estimate of prior immunity based on English data may not fit a NYC scenario, it is the only example of prior immunity to H1N1 we know of.

The continued high attack rate for the 5–14 age group reflects the absence of immunity for this age category, whereas the attack rate for the 65+ age group has halved. Figure 2 presents the epidemic curves for each of the two epidemics.

TABLE 6 Age-specific attack rates assuming no prior immunity in the baseline model and prior immunity consistent with the H1N1 epidemic

Age	Population	Baseline infection	Baseline AR	Prior immunity (%)	H1N1 infection	H1N1 AR
0–4	565,376	130,187	23.0	1.8	92,217	16.3
5–14	1,124,576	777,104	69.1	3.7	651,840	58.0
15–24	1,105,279	386,152	34.9	17.5	226,582	20.5
25–44	2,541,471	736,544	29.0	8.9	468,620	18.4
45–64	1,662,265	404,519	24.3	14.3	232,028	14.0
65–99	902,498	163,412	18.1	23.3	82,517	9.1
Total	7,847,465	2,597,918	33.0	*X*	1,753,804	22.3

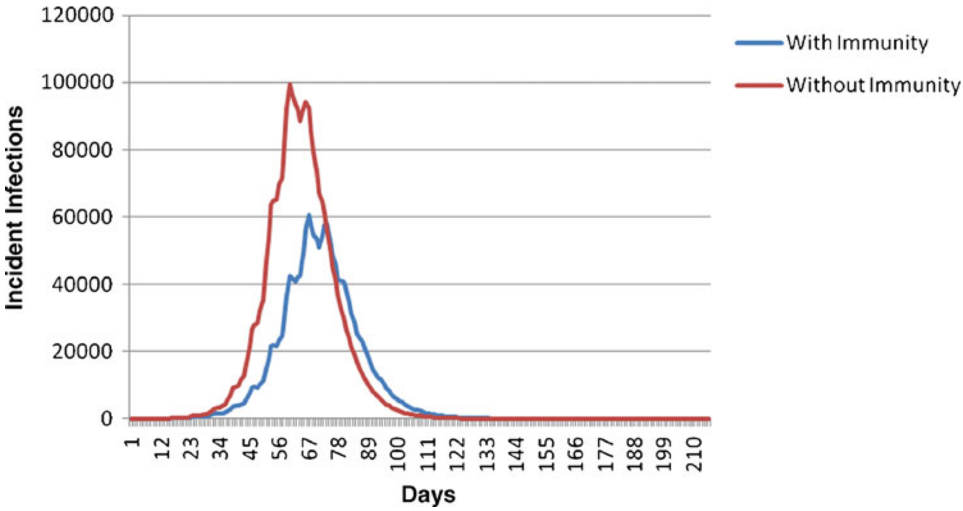

FIGURE 2. Baselines with and without prior immunity.

Interventions

Because we do not represent the bus-riding agents explicitly (they are included in community action), we do not examine explicitly the effects of reducing or eliminating subway service because that would result in subway riders switching to an alternative mode of travel. Instead, we simulated the "perfect" subway-targeted intervention by eliminating all infections occurring to all subway riders by other riders. This would illustrate the impact of a subway intervention of 100% effectiveness and would provide a frame of reference against which all related interventions could be compared.

Also, we do not simulate school closure as that has been studied by others (see Lee et al.[14]). Instead, we focus on social distancing behaviors as well as vaccination policies to explore the potential of reducing transmission for a fixed level of contacts. The contact-reducing policies would include:

Hand Washing, Microbial Use, and Mask Wearing on Subways We investigated the collective effects of restricting contacts only on subways. We do not argue that these are realistic, well-crafted interventions. Given the relatively low incidence of infections on subways (4.5%), we investigate whether any type of social distancing intervention would have sufficient effect to pursue their adoption. In the first instance, we assume that some combination of hand washing, microbial applications, and mask wearing that specifically targeted subway riders had the effect of reducing the effective number of contacts by a fixed percent. We further assume a 10%, 20%, or a 30% reduction in transmissions on subways. The impact of these assumptions is very small, as shown in Figure 3.

The subway-only interventions have a small effect on both the peak daily infection rate and the cumulative number of infections. Even the totally effective subway-targeted intervention only drops the peak 19% (from 104,944 to 84,604), and the cumulative infections decrease only 12% (from around 2,600,000 to 2,270,000; see Table 7). Because the portion of total infections that occur via the subway mixing process is sufficiently small, subway-targeted interventions can only have a limited effect on containing an epidemic.

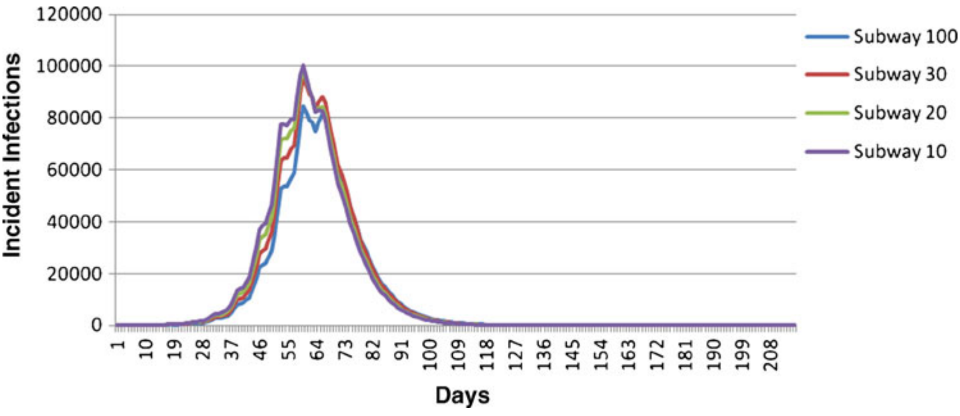

FIGURE 3. Impact of reducing contacts on subways for a $R_0=1.4$ epidemic assuming 10%, 20%, 30%, and 100% reductions in transmission rates.

Hand Washing, Microbial Use, and Mask Wearing Used in the Community We also simulated contact-reducing effects within the general community social network. These interventions assume that contact reductions occur on the subway as well as in the community at large, so naturally we would expect them to have a greater impact. As above, we investigated the effects of 10%, 20%, and 30% reductions in contacts, which are shown in Table 7.

In these scenarios, the interventions are directed at a larger segment of the population, i.e., they are not restricted to the population of subway riders. These larger impacts are best illustrated by noting that even a modest (10%) contact-reducing intervention in the community sector drops the peak infection by 19% and cumulative infections by 11%, which is comparable to a "totally effective" (100%) subway-targeted intervention.

Vaccination Programs We also evaluated a low-compliance vaccination program as a potentially effective intervention. We were motivated to analyze vaccination as an intervention strategy because Levine et al.[7] report that subway commuters specifically have lower vaccination rates than other segments of the population. Here, we do not specifically target subway riders nor limit our focus to contact

TABLE 7 Effect of NYC interventions

Intervention	Transmission rate reduction (%)	No. of infections at peak	Total no. of subway infections	Subway infections (%)	Total no. of all infections
None	0	101,557	114,377	4.41	2,596,176
Community	10	82,092	80,167	3.46	2,315,767
Subway	10	100,354	100,427	3.92	2,564,504
Vaccination	10	94,092	104,592	4.23	2,475,404
Community	20	75,047	75,047	3.64	2,060,896
Subway	20	97,974	87,434	3.48	2,512,033
Vaccination	20	90,754	97,688	4.13	2,362,695
Community	30	53,276	64,047	3.51	1,824,884
Subway	30	88,110	74,232	2.98	2,491,400
Vaccination	30	87,750	89,197	3.96	2,252,843
Subway	100	84,604	0	0.0	2,271,697

behaviors outside of the workplace and school. Instead, we simulate the effect of targeting all adults with a 10%, 20%, or a 30% vaccination rate that is applied on day 14 of the epidemic to all adults. The efficacy rate of the vaccine is assumed to be 80%. These results are also summarized in Table 7.

In summary, the most effective intervention is the process that targets the most people. That intervention is the community contact-reducing strategy which is more effective than the vaccination strategy because of its 100% compliance assumption.

CONCLUSION

In this study, we developed a unique influenza agent-based transmission model for NYC that explicitly represents subway riders as a transmission conduit. We calibrated our model to reconstruct a baseline epidemic that is characteristic of the 1957–1958 pandemic, but with the influence of subway riders on disease transmission also represented in the model. The results indicate that the proportion of total infections that occur on subways is between 4% and 5%. We also show that by incorporating immunity data into the baseline model, a transformation from the calibrated baseline model to an H1N1 2009 epidemic is suggested.

While computer models are simplifications of reality and cannot account for every possible factor or interaction, they can provide useful information to persons who must decide how to respond to possible epidemic scenarios and create response plans. For example, our model did not account for children commuting to school on the subway, nor did it distinguish between healthy and high-risk individuals who may become sicker and miss longer periods of work. Both of these factors may be important to decision makers. In addition, an influenza epidemic and the resulting circumstances may not necessarily conform to the data and assumptions that we drew from referenced sources or previously published models. Finally, the high rate of subway travel in the NYC metropolitan region may not be representative of other locations.

Our results indicate that the high level of subway ridership in NYC can influence disease spread, but that interventions aimed at subway riders would provide very limited benefits on overall attack rates and epidemic peaks. Even a highly unlikely intervention targeting all subway riders that provided 100% effectiveness (or, alternatively, subway service was suspended without side effects) would only reduce the cumulative incidence by 12.5%.

It is likely that the most effective policy to lower attack rates and the epidemic peaks is a policy that targets a broadest class of NYC residents. This is consistent with the targeted layered strategy demonstrated by others.[12]

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