Chapter 8
Understanding the Impact of Face Mask Usage Through Epidemic Simulation of Large Social Networks

Susan M. Mniszewski, Sara Y. Del Valle, Reid Priedhorsky, James M. Hyman and Kyle S. Hickman

Abstract Evidence from the 2003 SARS epidemic and 2009 H1N1 pandemic shows that face masks can be an effective non-pharmaceutical intervention in minimizing the spread of airborne viruses. Recent studies have shown that using face masks is correlated to an individual's age and gender, where females and older adults are more likely to wear a mask than males or youths. There are only a few studies quantifying the impact of using face masks to slow the spread of an epidemic at the population level, and even fewer studies that model their impact in a population where the use of face masks depends upon the age and gender of the population. We use a state-of-the-art agent-based simulation to model the use of face masks and quantify their impact on three levels of an influenza epidemic and compare different mitigation scenarios. These scenarios involve changing the demographics of mask usage, the adoption of mask usage in relation to a perceived threat level, and the combination of masks with other non-pharmaceutical interventions such as hand washing and social distancing. Our results shows that face masks alone have limited impact on the spread of influenza. However, when face masks are combined with other interventions such

S. M. Mniszewski (✉) · S. Y. Del Valle · R. Priedhorsky
Los Alamos National Laboratory, Los Alamos, NM 87545, USA
e-mail: smm@lanl.gov

S. Y. Del Valle
e-mail: sdelvall@lanl.gov

R. Priedhorsky
e-mail: reidpr@lanl.gov

J. M. Hyman and K. S. Hickman
Tulane University, New Orleans, LA 70118, USA
e-mail: myhyman@tulane.edu

K. S. Hickman
e-mail: khickman@tulane.edu

as hand sanitizer, they can be more effective. We also observe that monitoring social internet systems can be a useful technique to measure compliance. We conclude that educating the public on the effectiveness of masks to increase compliance can reduce morbidity and mortality.

1 Introduction

Pharmaceutical interventions such as vaccines and antiviral medication are the best defense in reducing morbidity and mortality during an influenza pandemic. However, current egg-based vaccine production process can take up to 6 months for the development and availability of a strain-specific vaccine and antiviral supplies may be limited. Fortunately, alternative strategies such as non-pharmaceutical interventions can reduce the spread of influenza until a vaccine becomes available. Face masks have been used to combat airborne viruses such as the 1918–1919 pandemic influenza [4, 29], the 2003 SARS outbreak [7, 38], and the most recent 2009 H1N1 pandemic [12]. These studies indicate that if face masks are readily available, then they may be more cost-effective than other non-pharmaceutical interventions such as school and/or business closures [13].

We focus on the use of surgical face masks and N95 respirators (also referred to as face masks). A surgical mask is a loose-fitting, disposable device that prevents the release of potential contaminants from the user into their immediate environment [8, 40]. They are designed primarily to prevent disease transmission to others, but can also be used to prevent the wearer from becoming infected. If worn properly, a surgical mask can help block large-particle droplets, splashes, sprays, or splatter that may contain germs (viruses and bacteria), and may also help reduce exposure of saliva and respiratory secretions to others. By design, they do not filter or block very small particles in the air that may be transmitted by coughs or sneezes.

An N95 respirator is a protective face mask designed to achieve a very close facial fit and efficient filtration of airborne particles [40]. N95 respirators are designed to reduce an individual's exposure to airborne contaminants, such as infectious viral and bacterial particles, but they are also used to prevent disease transmission when worn by a sick individual [20]. Typically, they are not as comfortable to use as a surgical face mask, and some health care workers have found them difficult to tolerate [23]. N95 respirators are designed for adults, not for children, and this limits their use in the general population.

Surgical masks and N95 respirators have been found to be equally effective in preventing the spread of influenza in a laboratory setting [20] as well as for health care workers [24]. In addition to reducing the direct flow of an airborne pathogen into the respiratory system the masks act as a barrier between a person's hands and face, which can reduce direct transmission.

A survey paper by Bish and Michie [5] on demographic determinants of protective behavior showed that compliance to using face masks is tied to age and gender. They observed that females and older adults were more likely to accept protective

behaviors than other population groups. Supporting these ideas, usage of face masks was consistently higher among females than male metro passengers in Mexico City during the 2009 Influenza A (H1N1) pandemic [12]. Limited studies suggest that there is more social stigmatization associated with wearing face masks in Western Countries than in Asia. For example, people rarely wear face masks in public in the United States, compared with their use in Japan and China [17]. An article published in 2009 by *New York Times Health* reported that "masks scare people away from one another" resulting in an unintentional social distancing measure [30] or "stay away" factor. Pang et al. showed that during the 2003 SARS outbreak, non-pharmaceutical interventions where implemented followed the epidemic curve [33]. That is, as the perception of SARS increased, more measures were implemented, and as the incidence declined, several measures were relaxed.

Based on these studies, we investigate the impact of face mask usage on the spread of influenza under several assumptions, including: (1) that females and older people will be more likely to wear them, (2) face mask wearers may follow the epidemic (e.g., the number of people wearing face masks depends on the incidence), and (3) face masks scare people away.

In order to transfer our results to the real world, it will be important to measure compliance. In the case of interventions such as face mask use, where individuals often choose to comply or not comply in the privacy of their daily lives, traditional methods of measuring compliance may be ineffective. Accordingly, we turn to social internet systems, specifically Twitter, where users share short text messages called *tweets*. These messages are directed to varying audiences but are generally available to the public regardless; they are used to share feelings, interests, observations, desires, concerns, and the general chatter of daily life. While other researchers have used Twitter to measure public interest in various health topics, including face masks as an influenza intervention [35], we carry out a brief experiment to explore the feasibility of using tweets to measure *behavior*.

The goal of this study is to understand the effectiveness of face mask usage for influenza epidemics of varying strengths (high, medium, low). A high level epidemic would be similar to the 1918–1919 H1N1 "Spanish flu" outbreak with large morbidity and mortality [32, 34, 42], a medium level would be similar to the 1957–1958 H2N2 Asian flu [15, 18], and a low level would be similar to the more recent 2009 Novel H1N1 flu [6, 10, 19]. We simulate face mask usage behavior through detailed large-scale agent-based simulations of social networks. These simulations have been performed using the Epidemic Simulation System (EpiSimS) [27, 28, 37] described in the next section.

2 Methods

2.1 Agent-Based Model Description

EpiSimS is an agent-based model that combines three different sets of information to simulate disease spread within a city:

- population (e.g., demographics),
- locations (e.g., building type and location), and
- movement of individuals between locations (e.g., itineraries).

We simulated the spread of an influenza epidemic in southern California with a synthetic population constructed to statistically match the 2000 population demographics of southern California at the census tract level. The synthetic population consists of 20 million individuals living in 6 million households, with an additional 1 million locations representing actual schools, businesses, shops, or social recreation addresses. The synthetic population of southern California represents only individuals reported as household residents in the 2000 U.S. Census; therefore, the simulation ignores visiting tourists and does not explicitly treat guests in hotels or travelers in airports.

We use the National Household Transportation Survey (NHTS) [44] to assign a schedule of activities to each individual in the simulation. Each individual's schedule specifies the starting and ending time, the type, and the location of each assigned activity. Information about the time, duration, and location of activities is obtained from the NHTS. There are five types of activities: *home*, *work*, *shopping*, *social recreation*, and *school*, plus a sixth activity designated *other*. The time, duration, and location of activities determines which individuals are together at the same location at the same time, which is relevant for airborne transmission.

Each location is geographically-located using the Dun and Bradstreet commercial database and each building is subdivided based on the number of activities available at that location. Each building is further subdivided into rooms or mixing places. Schools have classrooms, work places have workrooms, and shopping malls have shops. Typical room sizes can be specified; for example, for workplaces, the mean workgroup size varies by standard industry classification (SIC) code. The number of sub-locations at each location is computed by dividing the location's peak occupancy by the appropriate mixing group size. We used two data sources to estimate the mean workgroup by SIC, including a study on employment density [45] and a study on commercial building usage from the Department of Energy [26]. The mean workgroup size was computed as the average from the two data sources (normalizing the worker density data) and ranges from 3.1 people for transportation workers to 25.4 for health service workers. The average over all types of work is 15.3 workers per workgroup. For the analyses presented here, the average mixing group sizes are: 8.5 people at a school, 4.4 at a shop, and 3.5 at a social recreation venue.

2.2 Disease Progression Model

Airborne diseases spread primarily from person-to-person during close proximity through contact, sneezing, coughing, or via fomites. In EpiSimS, an interaction between two individuals is represented only by:

- when they begin to occupy a mixing location together,
- how long they co-occupy within a mixing place,
- a high-level description of the activity they are engaged in, and
- the ages of the two individuals.

A location represents a street address, and a room or mixing place represents a lower-level place where people have face-to-face interactions. When an infectious person is in a mixing location with a susceptible person for some time, we estimate a probability of disease transmission, which depends on the last three variables listed above. Details of social interactions such as breathing, ventilation, fomites, moving around within a sub-location, coughing, sneezing, and conversation are not included. Disease transmission between patients and medical personnel is not handled explicitly, and no transmission occurs when traveling between activities. Note that individuals follow a static itinerary, except when they are sick or need to care for a sick child. In this case, their schedule changes and all activities they were supposed to undertake are changed to *home*.

If susceptible person j has a dimensionless susceptibility multiplier S_j, infectious person I has an infectious multiplier I_i and T is the average transmissibility per unit time, then, $T S_j I_i$ will be the mean number of transmission events per unit time between fully infectious and fully susceptible people. The sum

$$\sum_j T S_j I_i$$

extends over all infectious persons that co-occupied the room with individual j. For events that occur randomly in time, the number of occurrences in a period of time of length t obeys a Poisson probability law with parameter.

$$\sum_j T S_j I_i t$$

Thus, the probability of no occurrences in time interval t is

$$e^{-\sum_j T S_j I_i t}$$

and the probability of at least one occurrence is

$$1 - e^{-\sum_j T S_j I_i t}$$

Using the mean duration t_{ij} of contacts between a susceptible person j and infectious person i, we assume that the probability that susceptible individual j gets infected during an activity is computed as:

$$P_j = 1 - e^{-\sum_j TS_j I_i t_{ij}} \tag{1}$$

Disease progression is modeled as a Markov chain consisting of five main epidemiological stages: uninfected, latent (non-infectious), incubation (partially infectious), symptomatic (infectious), and recovered. The incubation and symptomatic stage sojourn time distributions are described by a half-day histogram, giving respectively the fraction of cases that incubate for a period of between 0 and 0.5 days, 0.5 and 1.0 days, etc., before transitioning to the symptomatic or recovered stages, respectively. The average incubation time is 1.9 days and average duration of symptoms is 4.1 [25]. The influenza model assumes that 50 % of adults and seniors, 75 % of students, and 80 % of pre-schoolers will stay at home soon within 12 hrs of the onset of influenza symptoms. These people can then transmit disease only to household members or visitors. In addition, based on previous studies [25], we assume that 33.3 % of infections are subclinical where an infected individual is asymptomatic and shows no sign of infection. We modeled the subclinical manifestation as only half as infectious as the symptomatic manifestations. Persons with subclinical manifestations continue their normal activities as if they were not infected. The assumed hospitalization rate is a percentage of symptomatic individuals dependent on the strength of the pandemic. To simulate the higher attack rates seen in children, we assume that the infection rate in children was double that in adults. We analyze multiple scenarios for the same set of transmission parameters where the population was initially seeded with 100 people infected, all in the incubation stage.

2.3 Behavior Model

The behavior of each individual (agent) in an EpiSimS simulation is defined based on distributions for the effectiveness of their face mask usage in preventing infection to others (given as a distribution), effectiveness to preventing the individual from becoming infected (given as a distribution), acceptance of using the mask (given as a distribution), along with applicable age range, gender, and other possible demographic descriptive information. Effectiveness to others for mask usage is based on the protection factor of a mask type. It is the protection provided to people in contact with a sick individual wearing a mask. Effectiveness to self is based on the penetration level of a mask type. It is the protection provided to a healthy individual when in close contact with an infectious person. Distributions were used based on mask testing for the penetration level [2, 9, 21, 31] and protection factor [22]. Examples of these distributions are shown for N95 respirators in Table 1 and for surgical masks in Table 2. The effectiveness values drawn from each distribution are used to modify

Table 1 Effectiveness of N95 respirators in preventing an infected person from infecting others (protection factor) and the effectiveness of the face mask to prevent the wearer from being infected (penetration level) are listed along with the percentage of face mask users with this level of effectiveness from testing

Effectiveness to others (protection factor)	N95 respirator (%) users	Effectiveness to self (penetration level)	N95 (%) users
less than 0.1	0.00	less than 0.5	9.52
0.1	87.88	0.5	9.52
0.5	12.12	0.6	14.29
		0.7	14.29
		0.8	33.33
		0.9	19.05

Table 2 Effectiveness of surgical masks in preventing an infected person from infecting others (protection factor) and the effectiveness of the face mask to prevent the wearer from being infected (penetration level) are listed along with the percentage of face mask users with this level of effectiveness from testing

Effectiveness to others (protection factor)	Surgical mask (%) users	Effectiveness to self (penetration level)	Surgical mask (%) users
<0.1	91.67	0.1	13.89
0.1	8.33	0.2	8.33
		0.3	5.55
		0.5	5.55
		0.6	11.12
		0.7	38.89
		0.8	16.67

the infectivity (I_i) and susceptibility (S_j) between pairs contributing to whether or not transmission occurs.

As stated previously, age and gender play an important role in determining whether someone will comply with wearing a mask. The age ranges and compliance or acceptance by gender are based on values from a survey of behavior studies [5] and are shown in Table 3. Simulations that assigned mask usage by age and gender used the age ranges and acceptance in this table. Simulations that assigned mask usage randomly used constant acceptance values (e.g., 25 % of the population) for adults-only or all.

We assume that willingness to wear a mask is not influenced by a person being ill and the masks are only worn in non-home settings. Mask usage is initiated as an exogenous event, specified for a range of days. Usage can be specified as a fraction of all possible users (based on age and gender) and the duration can be specified as a distribution (e.g., constant, normal). Early in the simulations, each individual determines whether they will wear a mask based on age, gender, and acceptance. This is the pool of people from which mask users are selected. When we assume that mask usage will follow the course of an epidemic (e.g., disease perception increases

Table 3 Face mask
acceptance by gender and
age. Notice that the
willingness to use a face mask
increases with age and that
women are more willing to
use a face mask than men of
the same age

Age group	Males (%)	Females (%)
6–15	33	33
16–24	33	54
25–34	45	63
35–44	59	74
45–54	55	68
55–64	59	71
65–74	63	75
75+	57	72
Average	57	64

as incidence increases and vice-versa), mask usage ramps up and then down. For this
scenario, mask users change over time and some may use masks for a sequence of
days multiple times.

Scenarios that take into account a stay away factor used higher effectiveness
values based on assumptions regarding the amount of social distancing we expect
a mask wearer to experience (e.g., 30%). The mechanism we are assuming here is
that, in general, individuals will attempt to limit their contact with a person wearing
a mask. This translates to a larger histogram bin size for the distribution. Scenarios
where both surgical masks and hand sanitizer served as the mitigation strategy, do not
use the protection level and penetration factor values for effectiveness as described
previously, instead an effectiveness value of 50% is used based on an intervention
trial conducted at the University of Michigan [1].

2.4 The Reproduction Number

In epidemiological models, the effectiveness of mitigation strategies are often mea-
sured by their ability to reduce the effective reproduction number or replacement
number R_{eff}. R_{eff} is the average number of secondary cases produced by a typical
infectious individual during their infectious period [46]. In a completely susceptible
population and in the absence of mitigation strategies, the average number of sec-
ondary cases is referred to as R_0. The magnitude of R_0 determines whether or not
an epidemic will occur and if so, its severity. The number of infections grows when
R_0 is greater than one and it dies out when R_0 is less than one.

3 Results

We compare a base case scenario where no face masks are used for the high, medium,
and low epidemic levels with simulations using only face masks, face masks and hand
sanitizer (M and HS), and face masks coupled with social distancing (M and SD).

For the base case scenarios, we compare the epidemic parameters related to morbidity and mortality, including the attack rate, clinical attack rate, hospitalization rate, and mortality rate.

All of the scenarios that include face mask usage mitigations allow mask base acceptance by age and gender. Additionally, mask users follow the course of the epidemic incidence, increasing to the peak and then decreasing, ending 4 weeks after the peak. In support of this behavior, we present the results of a small experiment, where we use Twitter to estimate the shape of the compliance curve with respect to face masks.

Surgical masks and N95 respirators are considered independently in the face mask only scenarios, while surgical masks are the choice for the hand sanitizer and social distancing scenarios. N95 respirators can be more effective if both adults and children would use them, but they have not been designed for children and can be uncomfortable even for adults for long-term use. For these scenarios where mitigations are implemented, we compare the clinical attack rate, effective reproductive number, and for some cases, we show the the disease prevalence (symptomatic cases), incidence of mask users (new cases), and the effective reproductive number over time (R_{eff}).

3.1 Base Case Scenario

As described earlier, we used influenza epidemics of varying strengths (high, medium, low) to compare the impact of face mask usage on controlling the spread. These different levels share a similar disease progression as described in Sect. 2. The high level epidemic is based on the 1918–1919 H1N1 "Spanish flu" outbreak and has large morbidity and mortality [32, 34, 42], the medium level is based on the 1957–1958 H2N2 Asian flu [15, 18], and the low level is based on the more recent 2009 Novel H1N1 flu [6, 10, 19]. The number of hospitalizations and deaths were extrapolated from the U.S. population during the represented pandemic year to the U.S. synthetic population of 280M (based on 2000 census data). The attack rate (percentage of population infected), clinical attack rate (percentage of population symptomatic), hospital rate (hospitalizations out of population), and mortality rate (deaths out of population) are shown for each strength in Table 4. Figure 1 shows each of their respective epidemic curves for the new symptomatic as a function of time.

Table 4 Epidemic parameters associated with high, medium, and low strengths of epidemic

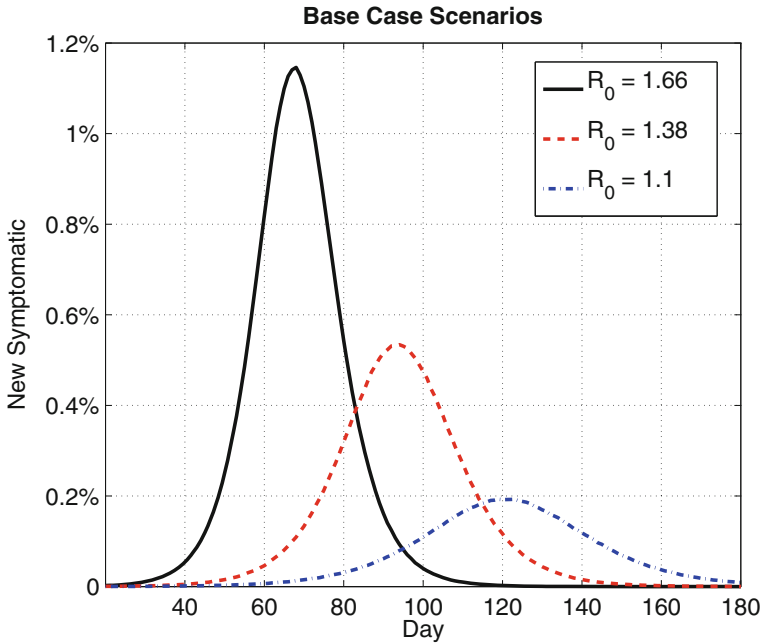| Epidemic level	Attack rate (%)	Clinical attack rate (%)	Hospital rate (%)	Mortality rate (%)
High	40.0	30.0	0.500	0.300
Medium	30.0	19.7	0.250	0.100
Low	20.0	10.0	0.008	0.015

Fig. 1 Base case simulation results for the three different epidemic strengths, showing the percentage of the population that becomes symptomatic per day

3.2 Using Twitter to Quantify Face Mask Usage

Our goal in exploring Twitter is to evaluate two conjectures: first, that the level of face mask wearing follows the disease incidence level, and second, that analysis of the public tweet stream is a feasible technique to measure compliance with face mask wearing (and, by implication, other behaviors relevant to infectious disease). To do so, we analyzed tweets published globally between September 6, 2009 and May 1, 2010, roughly corresponding to the H1N1 pandemic flu season in the United States.

There are 548,893,258 tweets in our dataset, an approximate 10 % sample of total Twitter traffic during this period. Of these, we selected the 75,946 which contained the word "mask"; in turn, a small fraction of these keyword matches—we estimate 3,350, or about 4.5 %—actually concern the medical face masks of interest to the present work (topics also include costume, sports, metaphor, cosmetics, movies, and others).

In order to identify these relevant tweets, we manually examined a random sample of 7,602 keyword matches (roughly 10 % of the total), coding them as (a) mentioning medical face masks (335 tweets), and perhaps additionally (b) sharing a specific observation that either the speaker or someone else is wearing, or has recently worn, a face mask (138 tweets).
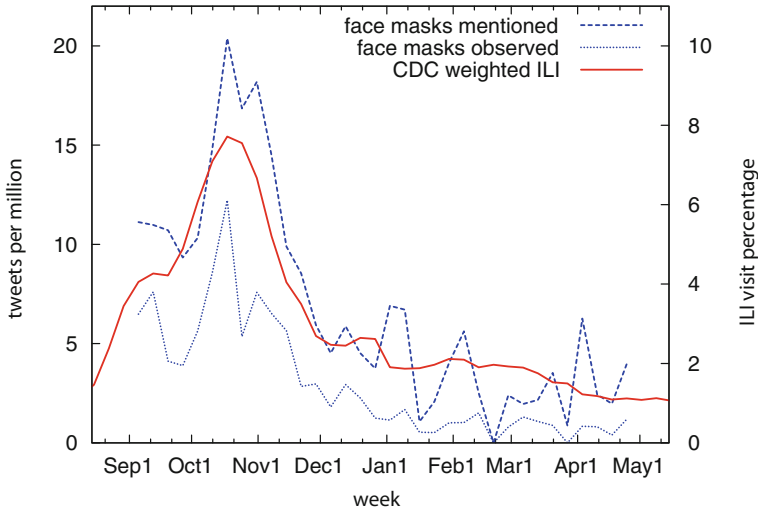
Fig. 2 Of each million tweets during the period September 6, 2009 through May 6, 2010, we show the number in which face masks are mentioned, as well as the subset of mentions which observe that someone specific is or was recently wearing a mask, whether the speaker himself or someone else. Also shown is the influenza-like illness rate from the CDC for the same period. The Pearson correlation between ILI rate and mentions is 0.92, and between ILI rate and observations is 0.90

Our results are shown in Fig. 2. As noted above, there are very limited survey studies that have collected information on mask use, especially from Western Countries [5]; accordingly, we compare our Twitter mention and observation counts against influenza-like illness (ILI) data published by the Centers for Disease Control (CDC) [11]. The correlation is excellent: 0.92 for mentions and 0.90 for observations.

These results have two implications. They provide empirical support for our assumption that face mask use is disease-dependent; that is, as disease incidence increases, face mask use increases, and as incidence decreases, so does mask use. Also, they suggest more broadly that social internet systems such as Twitter can, in fact, be used to measure disease-relevant behavior in the real world.

Challenges remain, however. First, we point out the severe signal-to-noise of these data: we identified just 20 out of every million tweets as relevant, even at the peak of the epidemic. Accordingly, analysis focusing on specific locales or demographic groups is not possible with this approach. Second, our manual coding approach clearly does not scale. Finally, we strongly suspect that information relevant to our specific questions (e.g., How many people are using face masks? Who are they? Where are they?) is contained in the vast number of tweets our coarse, preliminary approach discards as irrelevant. Our future work in measuring real-world behavior will go beyond simple keyword searches to leverage more sophisticated data mining algorithms.

Table 5 Attack rate parameters associated with high, medium, and low strengths of epidemic for face mask only scenarios starting when 0.01 % of the population is symptomatic

Epidemic level	Mask scenario	Attack rate (%)	Overall Clinical attack rate (%)	Mask users Clinical attack rate (%)
High	Surgical mask	34.22	25.66	14.24
	N95 respirator adults	35.03	26.27	12.74
	N95 respirator all	32.26	24.20	12.09
Medium	Surgical mask	24.51	16.35	7.40
	N95 respirator adults	25.55	17.04	7.03
	N95 respirator all	23.40	15.60	5.89
Low	Surgical Mask	16.35	8.18	2.88
	N95 Respirator Adults	17.69	8.85	2.80
	N95 Respirator All	16.96	8.49	1.73

3.3 Comparison of Intervention Strategies

Face mask only mitigation strategies were considered for surgical masks and N95 respirators separately. All scenarios began when 0.01 or 1.0 % of the population was symptomatic. Usage was based on age and gender and followed the course of the epidemic. Surgical masks were available to all age groups and N95 respirators to adults only and all age groups. Since N95 respirators were not designed for use by children, the adults only scenario is more realistic; however the all age groups scenario allows us to understand the importance of children wearing masks and the use of a more protective mask.

Scenarios with face mask usage starting when 1.0 % of the population was symptomatic resulted in higher attack rates and clinical attack rates than that for 0.01 % and will not be considered further here. Those starting at 0.01 % slowed the epidemic, allowing less burden to the public health system.

Table 5 shows the overall clinical attack rates for the epidemic as well as just for the mask users for all scenarios and epidemic strengths. Overall, only a small improvement is seen over the base case. The maximum mask users for all scenarios is 45–50 % of the population. Considering only the mask users, the clinical attack rates are much improved, with significant reductions for all three scenarios. The largest improvement is seen for N95 respirator where use is not limited to adults. This shows the importance of involving children in a face mask mitigation. Of the more realistic scenarios, surgical mask and N95 respirator adults, surgical mask performs best overall for all pandemic strengths, though worst when only considering mask users.

We compare the impact of combining face masks with hand sanitizers (M and HS) or with social distancing (M and SD). As described in Sect. 2.3, M and HS are assumed to reduce the transmission rate by 50 % and M and SD are assumed to reduced the transmission rate by 30 %. Figure 3, part A and C shows the epidemic curves when M and HS are implemented after 1.0 % of the population is symptomatic, and M and SD
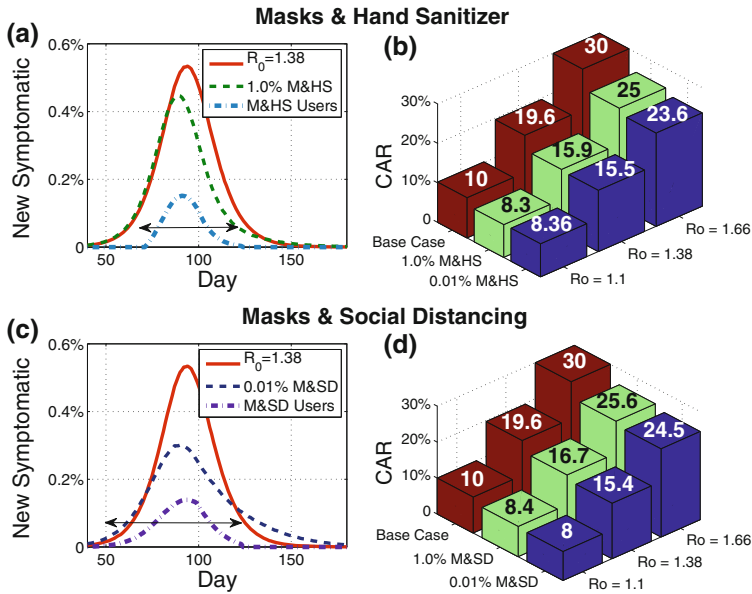
Fig. 3 Results of surgical masks and hand sanitizers (*top*) and masks and social distancing (*bottom*). **a** Epidemic curves for the base case, when the intervention is implemented after 1.0 % of the population is symptomatic, and the population that adopts the behavior (M and HS users). **b** Clinical attack rates (CAR) for the various pandemic levels and when masks and hand sanitizers are implemented after 1.0 and 0.01 % of the population is symptomatic. **c** Epidemic curves for the base case, when the intervention is implemented after 0.01 % of the population is symptomatic, and the population that adopts the behavior (M and SD users). **d** Clinical attack rates (CAR) for the base case, and two mask and social distancing scenarios for the different pandemic levels

when 0.01 % of the population is symptomatic, respectively. In addition to showing the overall dynamics of these two interventions, we show the epidemic curve for individuals who adopted the specified behavior, but who still became infected. Note that although the clinical attack rate was only reduced by 19 and 21 % for these two scenarios, the clinical attack rate for M and HS users was only 3.6 or an 81 % reduction. Similarly, the clinical attack rate for the M and SD users is 4.7 or a 76 % reduction from the base case. Part B and D, shows the clinical attack rate for various assumptions of the M and HS and M and SD scenarios and all the different pandemic levels.

From the results, it is clear that the earlier the interventions are put in place, the higher the impact they will have on reducing morbidity and mortality. Although these non-pharmaceutical interventions may not be very effective when compared to vaccines and antivirals, the overall impact for people that adopt these behaviors is significantly lower than the epidemic curve for the entire population. Table 6 takes the new clinical attack rate for the M and HS and M and SD intervention strategies and computes their difference. Then, this difference is expressed in the table as a percentage of the base case clinical attack rate for that epidemic strength. This

Table 6 Difference in clinical attack rate as a percent of base case clinical attack rate when comparing M and SD and M and HS intervention strategies

R_0	0.01 M and HS (%) 0.01 M and SD (%)	1.00 M and HS (%) 1.00 M and SD (%)	1.00 M and HS (%) 0.01 M and SD (%)	0.01 M and HS (%) 1.00 M and SD (%)
1.10	3.60	1.00	3.00	0.40
1.38	0.51	4.10	2.60	6.12
1.66	3.00	2.00	1.70	6.70

is meant to demonstrate the difference in the clinical attack rate relative to each intervention strategy on a scale that is proportional to the base case. If this percent is small then one could reasonably conclude that there is not much difference in the intervention strategies at that level. Overall, the scenarios with masks and hand sanitizer had a difference of less than 10 % of the base case clinical attack rate in all cases (see Table 7). The case of comparing M and HS implemented when 0.01 % of the population is symptomatic and M and SD when 1.0 % of the population is symptomatic is especially interesting at a low epidemic level, since the difference is less than 5 % even though M and SD has only a 30 % effectiveness compared to M and HS 50 % effectiveness. This motivates future studies into the difference in the effectiveness of these two intervention strategies at various epidemic strengths.

To better understand the overall effectiveness of the different intervention strategies we compare the effective reproduction number, R_{eff}, for five different scenarios:

- Surgical mask only (Mask),
- N95 respirators only-adults (N95 Adult),
- N95 respirators only-all (N95 All),
- Surgical masks and social distancing (Mask and Social Distancing), and
- Surgical masks and hand sanitizer (Mask and Hand Sanitizer).

All scenarios assume that the intervention begins when 0.01 % of the population is symptomatic, follows the course of the epidemic (ramping up to the peak and then down), and lasts 4 weeks after the peak. The likelihood of use of a non-pharmaceutical intervention, in each scenario, was dependent on age and gender as discussed previously.

Table 7 Percent reduction in clinical attack rate from base case at different epidemic strengths for M and HS or M and SD implemented at different epidemic levels

R_0	M and HS		M and SD	
	0.01 (%)	1.00 (%)	0.01 (%)	1.00 (%)
1.10	16.40	17.00	20.00	16.00
1.38	20.90	18.90	21.40	14.80
1.66	21.30	16.70	18.30	14.67

Note that at low epidemic levels, if implemented early, social distancing is competitive with hand sanitizing as an intervention strategy
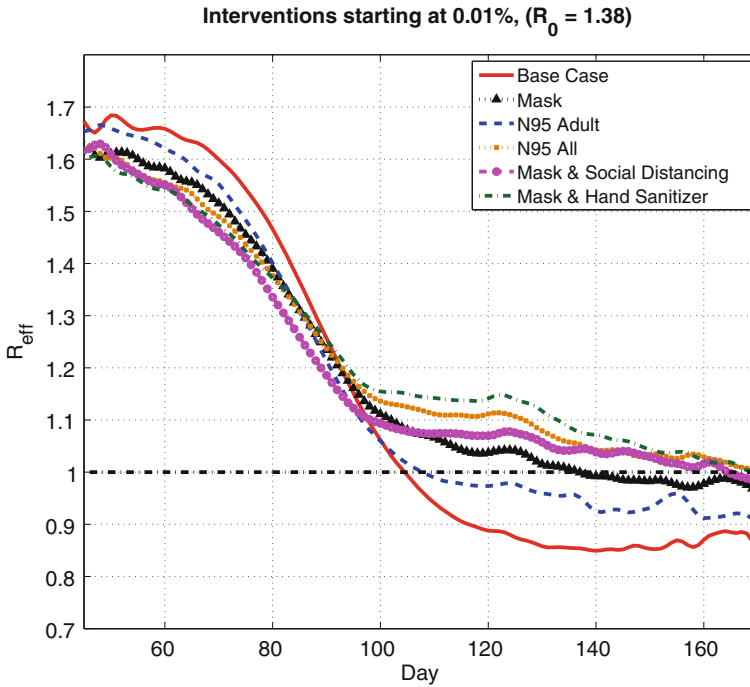
Fig. 4 R_{eff} over time as the epidemic progresses. For five different scenarios (shown starting from day 40), the dynamic behavior of R_{eff} is different. Intervention strategies cause the initial R_{eff} to be smaller than the base case, and then take longer to decrease below $R_{eff} = 1$. (The N95 Adult case has an initially higher R_{eff} than the other scenarios, presumably since children did not have intervention in this case.)

Figure 4 shows the change in the effective reproduction number, R_{eff}, over the course of the epidemic for the five scenarios described above during a medium ($R_0 = 1.38$) level outbreak. The basic reproduction number, R_0, is the average number of cases generated by a typical infectious individual in a completely susceptible population. Similarly, the effective reproduction number is the average number of cases generated by an infectious individual in a population that is not completely susceptible. The magnitude of the reproduction number determines whether or not an epidemic occurs and what its severity will be. When $R_0 > 1$, the number of infections grow and an epidemic occurs, and when $R_0 < 1$, the epidemic goes extinct.

We notice (Fig. 4) that for the different intervention strategies, the maximum R_{eff} is reduced. The exception is for the N95 scenario, N95 Adult, when children do not wear masks. In this case, R_{eff} shows a dramatic decrease but starts out high; this exception is not present if children wear the respirators as in N95 All.

4 Discussion

Non-pharmaceutical interventions such as face masks can play an important role in controlling the spread of airborne viruses. Based on historical observations, it is clear that some people wear face masks to protect themselves from infection. However, due to their limited effectiveness (known from filtration performance tests) the impact of face masks at the population level has not been well studied.

We used an agent-based simulation model to examine the effect that face masks alone, and in combination with other non-pharmaceutical interventions, has on reducing the spread of influenza. We analyzed the sensitivity with respect to various parameters including pandemic level, type of face mask, timing of intervention(s), and type of intervention.

Our results show that, in general, face masks have an impact on reducing the overall incidence and extending the length of the epidemic. Masks alone reduce the clinical attack rate, on average, by over 10 % for the entire population and 50 % for the population that wears face masks. Not surprisingly, our results show that face masks are more effective when coupled with other interventions. Although we expected that masks and hand sanitizers would have the largest return (given that we assume to be 50 % effective), social distancing performed almost as well as the hand sanitizer (even though we assume it was only 30 % effective). These observations imply that any mitigation that aims at reducing the probability of transmission, regardless of effectiveness, can contribute in reducing the overall impact of disease. Furthermore, the results are consistent with other studies concluding that the earlier interventions are put in place, the higher the impact they have on reducing morbidity and mortality.

We compare the effective reproduction numbers for various scenarios and show that intervention strategies cause the initial R_{eff} to be smaller than the base case and take longer to decrease below $R_{\text{eff}} = 1$. We also noted that the N95 case had an initially higher R_{eff} than the other scenarios due to the assumption that children would not wear N95 respirators.

For any intervention, it is important to measure the rate at which the intervention is actually happening. Non-pharmaceutical interventions such as face mask wearing presents special problems in this regard, because the decision to comply or not comply is an individual one which takes place away from observation by health providers. The intuition in exploring social internet systems such as Twitter to make these measurements is that the very high volume of observations, perceptions, and desires can, in aggregate, provide a sufficiently accurate measurement of compliance in real-world settings. Our preliminary results in analyzing Twitter are consistent with this intuition: we measured the use of face masks with a simple keyword-based approach, and both mentions of and observations of wearing face masks correlate strongly with CDC influenza incidence data. We expect future efforts to deepen this capability, providing results segmented by locale or demographics.

We conclude that for mathematical models of infectious diseases to be useful in guiding public health policy, they need to consider the impact of non-pharmaceutical

interventions. Face masks can be a cost-effective intervention when compared to closures; therefore, public health campaigns should focus on increasing compliance. Additionally, measuring the effect of these campaigns should include analysis of social internet systems and other emerging data sources. The results presented here are useful in providing estimates of the effects of non-pharmaceutical interventions on the spread of influenza.

References

1. Aiello, A.E., Perez, V., Coulborn, R.M., et al.: Facemasks, hand hygiene, and influenza among young adults: a randomized intervention trial. PLoS One **7**(1), e29744 (2012)
2. Balazy, A., Toivola, M., Adhikari, A. et al.: Do N95 respirators provide 95% protection level against airborne virus, and how adequate are surgical masks? Am. J. Infect. Control **34**(2), 51–57 (2006)
3. Barr, M., Raphael, B., Taylor, M. et al.: Pandemic influenza in Australia: using telephone surveys to measure perceptions of threat and willingness to comply. BMC Infect. Dis. **8**, 117 (2008)
4. Billings, M.: The influenza pandemic of 1918: the public health response. http://virus.stanford.edu/uda/fluresponse.html (2005). Accessed 26 April 2012
5. Bish, A., Michie, S.: Demographic and attitudinal determinants of protective behaviours during a pandemic: a review. Br. J. Health Psych. **15**, 797–824 (2010)
6. Bronze, M.S.: H1N1 influenza (swine flu). Medscape reference. http://emedicine.medscape.com/article/1807048-overview (2012). Accessed 27 April 2012
7. Brookes, T., Khan, O.A.: Behind the mask: how the world survived SARS, the first epidemic of the twenty-first century. American Public Health Association, Washington, DC (2005)
8. Brosseau, L., Ann, R.B.: N95 respirators and surgical masks. http://blogs.cdc.gov/niosh-science-blog/2009/10/n95/ (2012). Accessed 11 May 2012
9. Centers for Disease Control and Prevention: Laboratory performance evaluation of N95 filtering respirators, 1996. http://www.cdc.gov/mmwr/preview/mmwrhtml/00055954.htm#00003611.htm (1998). Accessed 26 April 2012
10. Centers for Disease Control and Prevention: CDC estimates of 2009 H1N1 influenza cases, hospitalizations and deaths in the United States, April 2009–January 16, 2010. http://www.cdc.gov/h1n1flu/estimates/April_January_16.htm (2010). Accessed 27 April 2012
11. Centers for Disease Control and Prevention: United States surveillance data: 1997–1998 through 2009–2010 seasons http://www.cdc.gov/flu/weekly/ussurvdata.htm (2010). Accessed 18 June 2012
12. Condon, B.J., Sinha, T.: Who is that masked person: the use of face masks on Mexico City public transportation during the influenza a (H1N1) outbreak. Health Policy (2009)
13. Del Valle, S.Y., Tellier, R., Settles, G.S., et al.: Can we reduce the spread of influenza in schools with face masks? Am. J. Infect. Control **2010**, 1–2 (2010)
14. Dimitrov, N.B., Goll, S., Hupert, N., et al.: Optimizing tactics for the use of the U. S. antiviral strategic national stockpile for pandemic influenza. PLoS One **6**(1), e16094 (2011)

15. Gani, R., Highes, H., Fleming, D. et al.: Potential impact of antiviral drug use during influenza pandemic. Emerg. Infect. Dis. **11**(9) (2005)
16. Greene, V.W., Vesley, D.: Method for evaluating effectiveness of surgical masks. J. Bacteriol. **83**, 663–667 (1962)
17. Hamamura, T., Park, J.H.: Regional differences in pathogen prevalence and defensive reactions to the "Swine Flu" outbreak among East Asians and Westerners. Evol. Psychol. **8**(3), 506–515 (2010)
18. Hilleman, M.R.: Realities and enigmas of human viral influenza pathogenesis, epidemiology and control. Vaccine **20**(25–26), 3068–3087 (2002)
19. Holdren, J.P., Lander, E., Varmus, H.: Report to the president on U. S. preparations for 2009– H1N1 influenza. http://www.whitehouse.gov/assets/documents/PCAST_H1N1_Report.pdf (2009). Accessed 27 April 2012
20. Johnson, D.F., Druce, J.D., Grayson, M.L.: A quantitative assessment of the efficacy of surgical and N95 masks to filter influenza virus in patients with acute influenza infection. Clin. Infect. Dis. **2009**(49), 275–277 (2009)
21. Lee, S.A., Grinshpun, S.A., Reponen, T.: Efficiency of N95 filtering facepiece respirators and surgical masks against airborne particles of viral size range: tests with human subjects. AIHAce 2005 (2005)
22. Lee, S.A., Grinshpun, S.A., Reponen, T.: Respiratory performance offered by N95 respirators and surgical masks: human subject evaluation with NaCl aerosol representing bacterial and viral particle size range. Ann. Occup. Hyg. **52**(3), 177–185 (2008)
23. Lim, E.C., Seet, R.C., Lee, K.H., Wilder-Smith, E.P., Chuah, B.Y., Ong, B.K.: Headaches and the N95 face-mask amongst healthcare providers. Acta. Neurol. Scand. **2006**(113), 199–202 (2006)
24. Loeb, M., Dafoe, N., Mahony, J. et al.: Surgical mask vs N95 respirator for preventing influenza among health care workers. JAMA **302**(17), 1865–1871 (2009)
25. Longini, I.M., Halloran, M.E., Nizam, A., Yang, Y.: Containing pandemic influenza with antiviral agents. Am. J. Epidemiol. **2004**(159), 623–633 (2004)
26. Michaels, J.: Commercial buildings energy consumption survey. http://www.eia.doe.gov/emeu/cbecs/cbecs2003/detailed_tables_2003/detailed_tables_2003.html (2003). Accessed 12 June 2012
27. Mniszewski, S.M., Del Valle, S.Y., Stroud, P.D., et al.: Pandemic simulation of antivirals + school closures: buying time until strain-specific vaccine is available. Comput. Math. Organ. Theor. **2008**(14), 209–221 (2008)
28. Mniszewski, S.M., Del Valle, S.Y., Stroud, P.D., et al.: EpiSimS simulation of a multi-component strategy for pandemic influenza. In: Proceedings of SpringSim, 2008
29. National Archives and Records Administration: The deadly virus: the influenza epidemic of 1918. http://www.archives.gov/exhibits/influenza-epidemic/index.html (2012). Accessed 26 April 2012
30. New York Times Health: Worry? Relax? Buy face mask? Answers on flu (2009). http://www.nytimes.com/2009/05/05/health/05well.html (2009). Accessed 26 April 2012
31. Oberg, T., Brosseau, L.M.: Surgical mask filter and fit performance. AJIC **36**(4), 276–282 (2008)
32. Osterholm, M.T.: Preparing for the next pandemic. N. Engl. J. Med. **352**(18), 1839–1842 (2005)
33. Pang, X., Zhu, Z., Xu, F., Guo, J., Gong, X., Liu, D., Liu, Z., Chin, D.P., Feikin, D.R.: Evaluation of control measures implemented in the severe acute respiratory syndrome outbreak in Beijing. J. Amer. Math. Assoc. 2003;290:3215 (2003).
34. Schoenbaum, S.C.: The impact of Pandemic Influenza, with Special Reference to 1918. International Congress Series **2001**(1219), 43–51 (2001)
35. Signorini, A., Polgreen, P.M., Segre, A.M.: The Use of twitter to track levels of disease activity and public concern in the U.S. during the influenza A H1N1 Pandemic. PLoS ONE **6**(5), e19467 (2011)
36. Stroud, P.D., Del Valle. S.Y., Mniszewski, S.M. et al.: EpiSimS pandemic influenza sensitivity analysis, part of the national infrastructure impacts of pandemic influenza phase 2 report. Los Alamos National Laboratory Unlimited Release LA-UR-07-1989 (2007)

37. Stroud, P., Del Valle, S., Sydoriak, S. et al.: Spatial dynamics of pandemic influenza in a massive artificial society. JASSS 10;4 9 http://jasss.soc.surrey.ac.uk/10/4/9.html (2007). Accessed 27 April 2012

38. Syed, Q., Sopwith, W., Regan, M., Bellis, M.A.: Behind the mask. Journey through an epidemic: some observations of contrasting public health response to SARS. J. Epidemiol. Community Health **2003**(57), 855–856 (2003)

39. U.S. Bureau of the Census: Historical U.S. population growth by year 1900–1998. Current population reports, Series P-25, Nos. 311, 917, 1095 http://www.npg.org/facts/us_historical_pops.htm (1999). Accessed 27 April 2012

40. U.S. Food and Drug Administration: Masks and N95 respirators. http://www.fda.gov/MedicalDevices/ProductsandMedicalProcedures/GeneralHospitalDevicesandSupplies/PersonalProtectiveEquipment/ucm055977.html (2010). Accessed 11 May 2012

41. U.S. News Staff: U.S. population, 2009: 305 million and counting. http://www.usnews.com/opinion/articles/2008/12/31/us-population-2009-305-million-and-counting (2012). Accessed 27 April 2012

42. U.S. Department of Health and Human Services: The great pandemic: the United States in 1918–1919. http://www.flu.gov/pandemic/history/1918/the_pandemic/index.html. Accessed 27 April 2012

43. U.S. Department of Homeland Security: Flu pandemic morbidity/mortality. http://www.globalsecurity.org/security/ops/hsc-scen-3_flu-pandemic-deaths.htm (2011). Accessed 27 April 2012

44. U.S. Department of Transportation (DOT): Bureau of transportation statistics NHTS 2001 highlights report BTS03-05. (2003)

45. Yee, D., Bradford, J.: Employment density study. Canadian METRO Council Technical Report (1999)

46. Van Den Driessche, P., Watmough, J.: Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. Math. Biosci. **180**, 29–48 (2002)