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Hand-Hygiene Mitigation Strategies Against Global Disease Spreading through the Air Transportation Network

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The risk for a global transmission of flu-type viruses is strengthened by the physical contact between humans and accelerated through individual mobility patterns. The Air Transportation System plays a critical role in such transmissions because it is responsible for fast and long-range human travel, while its building components—the airports—are crowded, confined areas with usually poor hygiene. Centers for Disease Control and Prevention (CDC) and World Health Organization (WHO) consider hand hygiene as the most efficient and cost-effective way to limit disease propagation. Results from clinical studies reveal the effect of hand washing on individual transmissibility of infectious diseases. However, its potential as a mitigation strategy against the global risk for a pandemic has not been fully explored. Here, we use epidemiological modeling and data-driven simulations to elucidate the role of individual engagement with hand hygiene inside airports in conjunction with human travel on the global spread of epidemics. We find that, by increasing travelers engagement with hand hygiene at all airports, a potential pandemic can be inhibited by 24% to 69%. In addition, we identify 10 airports at the core of a cost-optimal deployment of the hand-washing mitigation strategy. Increasing hand-washing rate at only those 10 influential locations, the risk of a pandemic could potentially drop by up to 37%. Our results provide evidence for the effectiveness of hand hygiene in airports on the global spread of infections that could shape the way public-health policy is implemented with respect to the overall objective of mitigating potential population health crises.

KEY WORDS: Air transportation network; behavioral changes; disease spreading; epidemic risk; human mobility networks; public health risk

1. INTRODUCTION

In past centuries, contagious diseases would migrate slowly, and rarely across continents. Black death, for example, which was the second recorded pandemic in history after the Justinian Plague, originated in China in 1334 (Centers for Disease Control and Prevention, 2015) and it took almost 15 years

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to propagate from East Asia to Western Europe. While contagious diseases were then affecting more individuals within countries, due to poor hygiene and underdeveloped medicine, the means of transportation of that era—sea and land—hindered the range and celerity of disease spreading. In contrast, current transportation means allow people to travel more often (either for business or for leisure) and to longer distances. In particular, the aviation industry has experienced a fast and continued growth, permitting an expanding flow of air travelers. In 2017 alone, around 4.1 billion people traveled through airports worldwide (International Civil Aviation Organization, 2018), while the International Air Transport Association (IATA) expects that the number of passengers will roughly double to 7.8 billion by 2036 (International Air Transport Association, 2017). Transportation hubs such as airports are therefore playing a key role in the spread of transmittable diseases (Brownstein, Wolfe, & Mandl, 2006; Hu, Li, Guo, van Gelder, & Shi, 2019). In severe cases, such disease-spreading episodes can cause global pandemics and international health and socioeconomic crises. Recent examples of outbreaks show how quickly contagious diseases spread around the world through the air-transportation network. Examples include the epidemic of severe acute respiratory syndrome (SARS) and the widespread H1N1 influenza. SARS initial outbreak occurred in February 2003, when a guest at a hotel in Hong Kong transmitted an infection to 16 other guests in a single day. The infected guests then transmitted the disease in Hong Kong, Toronto, Singapore, and Vietnam during the next few days, and within weeks the disease became an epidemic affecting over 8,000 people in 26 countries across five continents (Peiris, Guan, & Yuen, 2004; World Health Organisation, 2012). The H1N1 flu, which caused around 300,000 deaths worldwide (Dawood et al., 2012), had a similar timeline. The first confirmed case of H1N1 was reported in Veracruz, Mexico, on April 2009, while within few days the infection migrated to the United States and Europe, and two months later the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC) declared the disease as a global pandemic (Girard, Tam, Assossou, & Kieny, 2010).

Viruses are also transmitted easily at airports or during flights (Jones et al., 2009), causing infectious diseases to expand into global epidemics. Viruses may be transmitted through air, resulting in the contagion of airborne infections (Jones & Adida, 2011; Memish et al., 2014), or through physical contact between individuals (Nicas & Jones, 2009). The transmission is accelerated when dense populations are concentrated in confined spaces (Dalziel et al., 2018), like an airport, with lack of good hygiene and efficient air ventilation. After an outbreak, infections diffuse while infected individuals transmit the disease to susceptible individuals. Airports play a major role in such contagion dynamics (Colizza, Barrat, Barthélemy, & Vespignani, 2006; Lawyer, 2016), as they contribute daily to the contact of people from all over the world, some of whom may be carrying endemic infections from their country of origin. In addition, there are numerous highly contaminated surfaces that are frequently touched by passengers at airports and inside aircrafts (Ikonen et al., 2018). Self-service check-in screens, gate bench armrests, water fountain buttons and door handles at airports, as well as seats, tray tables, and handles of lavatories in aircrafts, are all known to have high microbial contamination (McKernan, Burge, Wallingford, Hein, & Herrick, 2007; Schaumburg, Köck, Leendertz, & Becker, 2016; Zhao et al., 2019).

Mitigation strategies are designed and implemented to inhibit global pandemics. At the level of individuals, there is a focus on behavioral change toward adopting different interventions in the event of a health emergency (Poletti, Ajelli, & Merler, 2011; Verelst, Willem, & Beutels, 2016). Along with other developments in medicine, vaccination has made a big contribution in that direction, leading to the extinction of past epidemics and to a significant reduction of mortality due to specific infections (Greenwood, 2014). Vaccination has a substantial mitigating effect when effective vaccines are available soon enough after the emergence of a new disease, and when vaccination campaigns cover about 70% of a susceptible population (Yang et al., 2009). However, despite the known impact of vaccines on the reduction of infections, the rate of vaccination in the population has remained unchanged over the past decade (Yokum, Lauffenburger, Ghazinouri, & Choudhry, 2018). Social nudges such as peer effects or education on vaccination benefits, and changes in the design of vaccination campaigns, can be deployed to change human behavior toward the increase of influenza vaccination rates (Patel, 2018). In addition of preventing disease spreading by vaccination, isolating patients at home or closure of high-risk places like schools can moderate the transmission of disease-causing pathogenic microorganisms.

Several actions within the world air-transportation network can be implemented to control disease spreading in the event of a health emergency (Huizer, Swaan, Leitmeyer, & Timen, 2015). At the global scale, mobility-driven interventions such as airport closures and deliberate rerouting of the travelers can reduce the number of individuals passing through or traveling from/to regions where dangerous diseases prevail (Nicolaides, Cueto-Felgueroso, & Juanes, 2013). At the local scale, actions within each airport, including the frequent cleaning of public areas (e.g., toilets, gates, check-in desks), efficient air ventilation, and enhanced sanitization of frequently touched surfaces can reduce the risk of contamination and the rate of transmission of infections. Furthermore, personal hygiene is among the most important factors to prevent the spread of an infection (Aiello & Larson, 2002; Aiello, Coulborn, Perez, & Larson, 2008; Null et al., 2018; Rabie & Curtis, 2006; Wong, Cowling, & Aiello, 2014). Coughing etiquette, face masks (Brienen, Timen, Wallinga, Van Steenbergen, & Teunis, 2010), no face touch, and hand hygiene are the most common actions that air travelers can easily adopt. From those actions, hand washing is simple and therefore is regularly mentioned as the first recommendation during disease spreading (World Health Organisation, 2009). A scientific study on the effects of hand washing on the bacterial contamination of hands showed that, after a deliberate contamination of individuals by touching door handles and railings in public places, bacteria were found in 44% of the sample. This percentage was reduced to 23% after hand washing with water alone, and to 8% after hand washing with water and plain soap (Burton et al., 2011). The same study showed that the effect of hand washing does not depend on the bacteria species.

While hand hygiene is considered as the first prevention step in the case of an epidemic emergency, there is lack of evidence for its effects as a mitigation strategy against global epidemic spreading. In this work, we study contagion dynamics through the world air-transportation network, and we elucidate the impact of hand-hygiene behavioral changes on the diffusion of infections worldwide. We develop a computational model that simulates the realistic mobility of air travelers through the air-transportation system, coupled with the propagation of a hypothetical infectious disease. Human mobility is modeled by a stochastic agent-based system that accounts for the spatial distribution of airports, realistic patterns of human mobility through the world air-transportation network, and the data-driven waiting-time distributions of individuals at origin, destination, and connecting airports. Using world air-traffic data, we first generate the worldwide air-transportation network, where the nodes are the 2,500 busiest airports and the links between them are given by the connections between airports for which flights exist in the data set. The network describes a heterogeneous metapopulation of airports where each individual airport is a subpopulation of individuals (Brockmann & Helbing, 2013; Balcan et al., 2009; Colizza, Pastor-Satorras, & Vespignani, 2007). We further develop a compartmental epidemic model to track the reaction dynamics of infection contagions as well as the hand-washing–related behavior of the traveling agents.

Using Monte Carlo simulation, we assess the impact of hand washing at the early stages of a global epidemic. From the simulation results we measure the early-time spreading power of the 120 busiest airports under four different intervention scenarios: (1) increase of hand-washing engagement homogeneously at all airports; (2) increase of hand-washing engagement only at the source of the disease; (3) increase of hand-washing engagement at the 10 most important airports of the world air-transportation network; and (4) increase of hand-washing engagement at the 10 most important airports for each source of the disease. The aim of this study is to identify the most effective mitigation strategy of hand hygiene contributing the most to the reduction of global epidemic risk.

2. MATERIALS AND METHODS

2.1. Data Description

We use world air-traffic data provided by the Official Airline Guide (OAG), that includes all the trips (more than 1.9 million) that were booked in September 2017. Each row in the data set states the number of passengers that traveled from an origin airport to a destination airport, and indicates any intermediate connecting flights (see Table I for example).

From the data set, we observe that all trips in September 2017 were operated through a network of 3,621 unique airports. For each airport, we estimate the total traffic by adding the number of passengers for the trips where the airport is denoted as "Origin," the number of passengers for the trips where the airport is denoted as "Destination," and twice the

Table I. An Example of Air-Traffic Data Showing that in September 2017 X1 Individuals Traveled with Direct Flights from PEK (Beijing, China) to HND (Haneda, Japan), X2 Individuals Traveled from PEK to HND with a Layover at PVG (Shanghai, China), and X3 Individuals Traveled from ATL (Atlanta, USA) to ABV (Abuja, Nigeria) with Connecting flights at JFK (New York, USA) and CDG (Paris, France) Airports

Origin	Connection 1	Connection 2	Destination	Passengers
⋮	⋮	⋮	⋮	⋮
PEK	–	–	HND	X1
PEK	PVG	–	HND	X2
ATL	JFK	CDG	ABV	X3
⋮	⋮	⋮	⋮	⋮

number of passengers for the trips where the airport is denoted as "Connection" (either Connection 1 or 2). For subsequent computational efficiency, we restrict our analysis to the subset of the data set corresponding to traffic among the 2,500 *busiest* airports (by total traffic). This subset accounts for 98.25% of the total trips and 99.8% of the total traffic.

2.2. Mobility Model

The human mobility model has the form of a stochastic agent-based tracking system (González, Hidalgo, & Barabási, 2008; Nicolaides, Cueto-Felgueroso, González, & Juanes, 2012) that accounts for the spatial distribution of airports, the detailed air-traffic data, the correlated and recurrent nature of human mobility, and the waiting-time distributions of individuals at different locations. We first generate the origin–destination *flux* matrix $\mathbf{OD^f} = [od_{ij}^f]$, where od_{ij}^f is the number of passengers that traveled in September 2017 from origin i to destination j, and the origin–destination *probability* matrix $\mathbf{OD^p} = [od_{ij}^p]$, where od_{ij}^p is the probability that an agent travels from origin i to destination j. Each element of the $\mathbf{OD^p}$ matrix is calculated as $od_{ij}^p = od_{ij}^f / \sum_j od_{ij}^f$, where $\sum_j od_{ij}^f$ is the total number of passengers that traveled from origin i. We then assign a "home" population, P_i, at each subpopulation, i, following the nonlinear empirical relation $P_i = \alpha\sqrt{T_i}$, where T_i is the total traffic at airport i, and α is a constant that is adjusted to give a total population size of $N = \sum_i P_i$ individuals. In other words, each individual agent is initially assigned to its "home" subpopulation i. Within the mobility route, the agent that was assigned to home i chooses to travel at a "destination" airport j with probability extracted from the $\mathbf{OD^p}$ matrix. If the two nodes i and j are connected by more than one path (i.e., direct when the two airports are connected with direct flights and indirect when the two airports are connected only with connecting flights), then the probability that the agent selects a given path is proportional to the relative number of passengers traveling in each direct or indirect flight from origin i to destination j. After each trip (from origin i to destination j), the agent returns back to its home airport. Hence, the stochastic mobility model generates the spatial trajectory for all agents. In addition, using realistic waiting times at the three distinct locations where an agent can be (i.e., home, connecting airport, or destination) and actual flight times required to travel between the airports, we express the spatiotemporal patterns of all the agents at the granularity of an hour. The waiting times at home airports, connecting airports, and destinations are provided by the Bureau of Transportation Statistics 2010 (Barnhart, Fearing, & Vaze, 2014), and follow right-skewed distributions with means 897.87 hours (∼37 days), 1.33 hours, and 127.36 hours (∼five days), respectively. The average flight time from airport i to airport j is estimated as the ratio of the geographical distance between the two airports, d_{ij}, which is calculated by the spherical law of cosines, over the average velocity of an airplane, which is assumed to be constant and equal to 640 km/hour considering the changes in takeoff, climb, cruise, descent, and landing speeds.

2.3. Epidemic Model

The conventional SIR model in epidemiology describes the reaction kinetics of infectious diseases (Vespignani, 2012). According to the SIR model, each individual is considered as either *susceptible* (S), *infected* (I), or *recovered* (R). The sum of the compartments at any given time t is equal to the total population size ($S(t) + I(t) + R(t) = N$). The SIR model describes two distinct processes: the infection process, $S + I \xrightarrow{\beta_1} 2I$, where an infected individual transmits the infection to a susceptible individual with rate β; and the recovery process, $I \xrightarrow{\mu} R$, where an infected individual recovers with rate μ (μ^{-1} is the average time required for an infected individual to recover). The ratio $R_0 = \beta/\mu$ defines the basic reproductive number of the infection, that is, the average number of secondary infections an infected individual causes before it recovers. For a closed population,

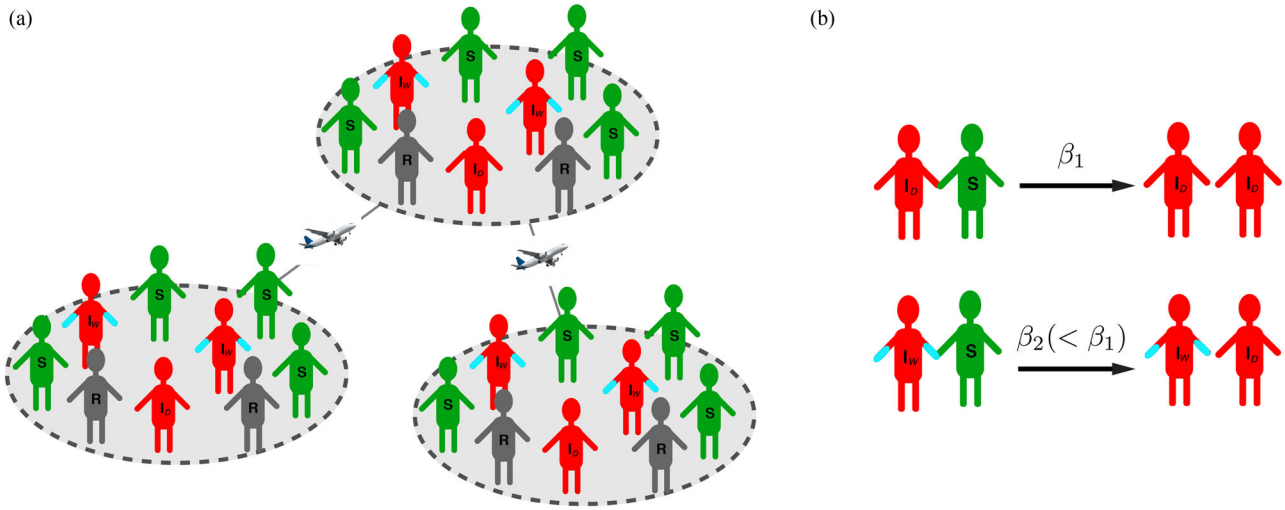

Fig. 1. Pictorial demonstration of our model. (a) Illustration of the SIR_{WD} traveling population. Each individual can be either Susceptible to the disease, Recovered from the disease, Infected-Washed (blue hands), or Infected-Dirty. (b) Schematic diagram of the SIR_{WD} infection reaction. When an Infected-Washed individual comes in contact with a susceptible individual, the probability of transmitting the disease is smaller compared to the case when the infected individual has "dirty" hands.

the infection dies out exponentially fast when $R_0 < 1$, while it grows and potentially causes a pandemic for $R_0 > 1$ (Liu et al., 2018).

In this study, we modify the conventional SIR model to reflect the effects of hand washing in the infection process. We formulate the SIR_{WD} model, where each individual is placed in one of the three epidemic compartments (susceptible, infected, recovered), and it is also categorized into one of the two hand-cleanliness states, namely, *washed* (W) or *dirty* (D) (Fig. 1(a)). The SIR_{WD} epidemic model is then expressed as:

$$S + I_D \xrightarrow{\beta_1} 2I,$$
$$S + I_W \xrightarrow{\beta_2} 2I,$$
$$I \xrightarrow{\mu} R,$$
$$D \xrightarrow{p} W,$$
$$W \xrightarrow{\theta} D,$$

where β_1 is the infection rate with which an infected individual with *dirty* hands transmits the infection to a susceptible individual (β_1 is equal to the infection rate β of the conventional SIR model), β_2 is the infection rate with which an infected individual with *washed* hands transmits the infection to a susceptible individual ($\beta_2 < \beta_1$), μ is the recovery rate (it is equal to the recovery rate of the conventional SIR model), p is the hand-washing engagement rate (denoting the percentage of individuals with nonclean hands that move to the washed state within the next hour), and θ is the hand-washing effectiveness rate (θ^{-1} denotes the average time needed for an individual with washed hands to return back to the *dirty* state). The infection rate β_2, with which an infected individual with *washed* hands transmits the infection to a susceptible individual, is reduced compared to the base infection rate β_1. The percentage reduction parameter, λ, is such that $\beta_2 = (1 - \lambda)\beta_1$. The infection reactions that are described in the first two expressions of the SIR_{WD} model are shown in Fig. 1(b).

To be infected, a healthy individual needs to touch a contaminated surface or come into contact directly with an infected person. If the individual is healthy and touches a contaminated surface—regardless of how long ago he/she washed his/her hands—he/she will get the bacteria on hands. However, if he/she washes hands soon after he/she gets contaminated, there is a significant probability of removing that bacteria from the hands before being transmitted to body fluids. Therefore, the hand-washing rate of healthy individuals affects the transmissibility of a disease. The SIR_{WD} model takes into account only the interdependence between disease transmission probability and the hand cleanliness of the infected individuals. To model the process where the hand-washing behavior of susceptible/healthy individuals plays a role in the infection process, we need to build a more sophisticated model

based on SEIR reaction kinetics, where the extra epidemic compartment, E, denotes individuals that are *Exposed* to the infection (Brauer, 2017). The SEIR epidemic model describes the following three processes: (1) a susceptible individual comes in contact with an infected one and becomes exposed to the disease with some rate β ($S + I \xrightarrow{\beta} E + I$); (2) an exposed individual becomes infected with some rate γ ($E \xrightarrow{\gamma} I$); and (3) an infected individual recovers with rate μ ($I \xrightarrow{\mu} R$). Both rates, β and γ, are affected by the hand-washing levels. We keep our analysis simple by using the conventional SIR model with the assumption that if infected individuals wash their hands frequently, there is a smaller probability to contaminate surfaces or other healthy people directly.

2.4. Initial Conditions and Assumptions

We assume a flu-type disease, where the recovery rate is $\mu = 1/4$ days^{-1} (i.e., on average each infected individual recovers after four days) and the reproductive number is $R_0 = 3$ (i.e., on average each infected individual transmits the disease to three other individuals). The infection rate in the SIR model is $\beta = \mu R_0$, which is equal to the infection rate, β_1, of the processes $S + I_D \xrightarrow{\beta_1} 2I$ in the SIR_{WD} model. The infection rate of the process $S + I_W \xrightarrow{\beta_2} 2I$ is equal to $\beta_2 = (1 - \lambda)\beta_1$, where λ is the percentage reduction parameter of the infection rate due to hand washing. A previous study stated that effective hand washing can prevent 50% to 70% of waterborne and foodborne infections (Lee, Hong, & Kim, 2015). However, there is a limitation in the number of studies that measure experimentally the effect of hand washing on the reduction of airborne or direct-contact infections. Here, we initially set the value of λ equal to 0.4 and we further investigate its variation in Section 3.3. The hand-washing effectiveness rate, θ (whose inverse sets the average duration before washed hands become again contaminated), is initially set to $\theta = 1/1.5$ hours^{-1}. We investigate the sensitivity to this parameter in Section 3.3. We consider that at most one in five people in an airport have cleaned hands at any given moment in time (i.e., 20% of airport population). This is equivalent to hand-washing engagement rate among the noncleaned individuals equal to $p = 0.12$ per hour (i.e., every hour about 12% of the noncleaned individuals are washing their hands). We declare this hand-washing engagement rate ($p = 0.12$ hours^{-1}) as the *status quo* as we discuss it at the Section 2.5. We vary p to analyze and quantify the effect of hand-washing engagement on different scenarios of epidemic spreading.

2.5. Status Quo of Hand-Washing Engagement Rate

To derive an approximation of the *status quo* level of hand cleanliness (i.e., the percentage of people with cleaned hands) in the population of an airport at any given moment, we simulate the dynamics of a closed population following some assumptions derived from the literature. We use data from a survey performed by the American Society for Microbiology (2003), which revealed that 30% of travelers do not wash their hands after using the public toilets at airports, implying that the remaining 70% are compliers with hand washing. Following a study in a college town environment, we consider that only the 67% of the compliers wash their hands properly (i.e., with water and soap and for the recommended by CDC duration of time; Centers for Disease Control and Prevention, 2016), while the remaining 33% are wetting their hands quickly and/or without soap (Borchgrevink, Cha, & Kim, 2013). Therefore, we assume that in an airport population of N individuals, only the $70\% \cdot 67\% = 49.6\%$ of N are compliers with effective hand washing. Furthermore, we assume that each individual washes his/her hands on average between 4 and 10 times per day (Merk, Kühlmann-Berenzon, Linde, & Nyrén, 2014), which means that in a 24-hour time frame, one event of hand washing takes place every 2.5–6 hours. We assume that the frequency of hand washing follows a normal distribution with mean equal to 4.5 hours and standard deviation equal to 1 hour. We also consider that the duration of cleanliness of hands after hand washing follows an exponential distribution with mean value equal to 1.5 hours.

Using the above approximations, we find that at any given moment, the percentage of passengers in an airport that have cleaned hands has an *upper bound* of 24%. Given that this is a very optimistic upper bound of the reality, we assume and use in simulations that the *status quo* for the percentage of individuals that have clean hands in an airport at any given moment is 20%. To preserve a stable 20% hand-cleanliness level over time in an airport, the *hand-washing engagement rate* in the compartmental SIR_{WD} model, that indicates the rate of hand washing per hour between individuals with noncleaned hands, is calculated to be equal to $p = 0.12$ hour^{-1} (i.e.,

12% of "dirty" individuals wash their hands within an hour). This indicates the *status quo* of hand-washing engagement rate. In the case that we would like to increase the level of hand cleanliness in an airport to 30% or 40% or 50% or 60% we need to increase the hand-washing engagement rate to 0.21 hour^{-1} or 0.32 hour^{-1} or 0.49 hour^{-1} or 0.73 hour^{-1}, respectively.

2.6. Monte Carlo Simulations

We implement the epidemic model within the mobility model using Monte Carlo simulation to track the mobility and contagion dynamics through the air-transportation network. In the simulations we consider different hand-hygiene mitigation strategies, and study their effects on the propagation and diffusion of a disease at the global scale. We first study the conventional SIR epidemic model to identify the spatiotemporal structure of the disease for different seeding scenarios and to identify the most influential spreaders within the air-transportation network. Furthermore, we study four hand-hygiene scenarios and their effectiveness toward disease spreading inhibition: (1) homogeneous increase of hand-washing engagement at all airports, (2) increased hand-washing engagement at the 10 most influential airports in the network, (3) increased hand-washing engagement at the 10 most influential airports for each source of the disease, and () increased hand-washing engagement only at the source of the disease.

At the initial time step of each simulation, $t = 0$, we declare an airport i as the source of the disease where we randomly choose 10 individuals to seed the infection. For each analysis, we run 100 realizations of 10^5 traveling agents each. At each time step, which corresponds to *one hour*, we let individuals travel, wash their hands, and recover or transmit the disease to susceptible agents when those individuals are infected. At each time step, an infected individual recovers with probability $\Pi_{I \to R} = 1 - \exp(-\mu)$. When the transmission of an infection is associated with hand cleanliness of the infected individuals (as described by the $\mathrm{SIR_{WD}}$ model), the probability of a susceptible to get the infection is $\Pi_{S \to I} = (1 - (1 - \beta_1/N_i)^{I_{D,i}}) + (1 - (1 - \beta_2/N_i)^{I_{W,i}}$, where $I_{D,i}$ and $I_{W,i}$ are the numbers of "dirty" and "washed" infected individuals, respectively, at airport i and N_i is the total population at airport i. The probability that an individual with washed hands becomes "dirty" is $\Pi_{W \to D} = 1 - \exp(-\theta)$ and the probability that an individual with "dirty" hands will wash his/her hands, within each one-hour time step, is $\Pi_{D \to W} = 1 - \exp(-p)$. Using these probabilities, the computational model generates the stochastic epidemic transitions for the traveling agents over time. In our analysis, we vary the model parameter p, considering different hand-hygiene interventions, and analyze their impact on global disease spreading.

2.7. Evaluating the Early-Time Impact of the Disease

We evaluate the early-time impact of the disease by measuring two quantities that are correlated: the *disease prevalence* and the *Total Square Displacement* (TSD) two weeks after the disease is deliberately seeded in a source. The disease prevalence (PREV) is given by the total number of affected individuals (infected plus recovered) (Rothman, 2012). However, as we wish to evaluate not only the total number of infected individuals but also how well spread they are within the globe, we use the TSD of the infected individuals as a simulation metric (Nicolaides et al., 2012). This metric is given by the formula $TSD = \sum_{j=1}^{I(t)} (L_j - \langle L \rangle)^2$, where $I(t)$ is the number of infected individuals at time $t = 2$ weeks, L_j is the geographic location of the jth infected individual, and $\langle L \rangle$ is the position of the geographic center of the infection. The geographic center is the center of gravity (aka the center of mass) for the locations of all infected individuals. To find the geographic center, we first convert the latitude and longitude of each location L_j from degrees to radians, and then into Cartesian coordinates using the formulas: $x_{L_j} = \cos(lat_{L_j}\pi/180) \cdot \cos(lon_{L_j}\pi/180)$, $y_{L_j} = \cos(lat_{L_j}\pi/180) \cdot \sin(lon_{L_j}\pi/180)$, and $z_{L_j} = \sin(lat_{L_j}\pi/180)$. We then calculate the mean of the Cartesian coordinates by $x = \sum_{j=1}^{A(t)} x_{L_J}$, $y = \sum_{j=1}^{A(t)} y_{L_J}$, and $z = \sum_{j=1}^{A(t)} z_{L_J}$, and finally we convert the average coordinates (x, y, z) into latitude and longitude in radians using the four-quadrant inverse tangent function $\langle L \rangle = ((180/\pi) \cdot \mathrm{atan2}(z, \sqrt{x^2 + y^2}), (180/\pi) \cdot \mathrm{atan2}(x, y))$.

3. RESULTS

3.1. Conventional SIR Model

In our initial analysis, we first use the SIR model (considering that the infection reaction process is independent from the hand cleanliness of the infected

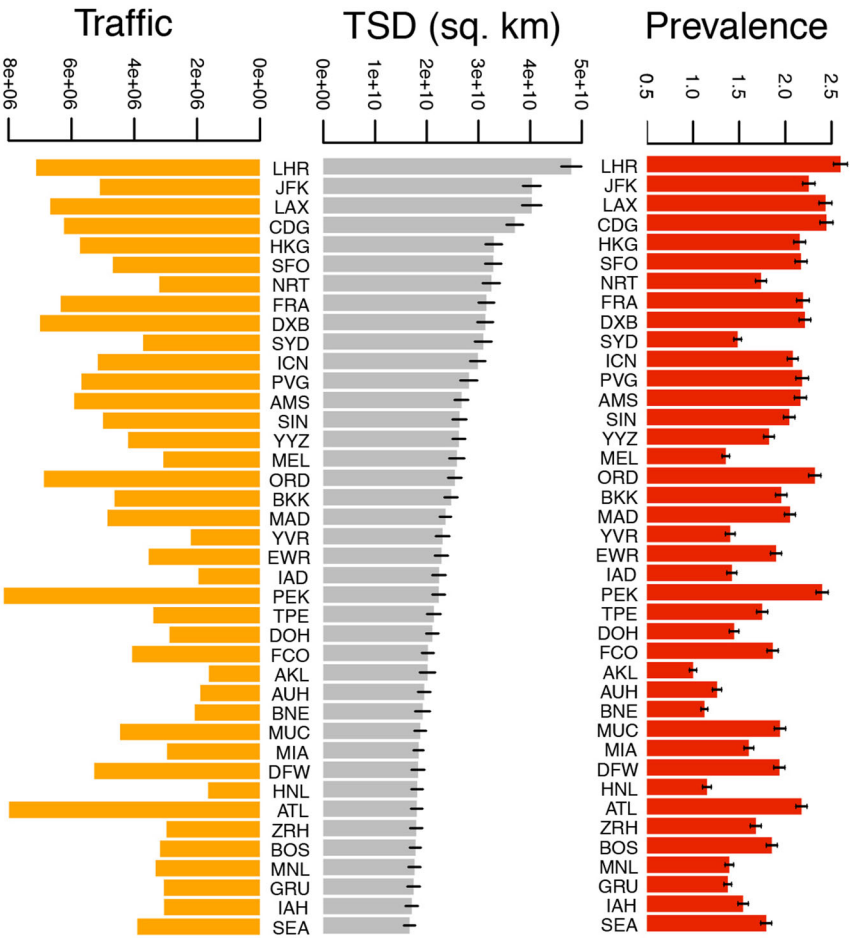

Fig. 2. The impact of the source of the disease on its global spread. (Middle) Ranking of the 40 most influential airports in the world with respect to the TSD of the infected individuals two weeks after the disease started from each one of these airports. (Right) The two-week prevalence of the disease as measured by the percentage of world population that have been affected (infected plus recovered) by the disease two weeks after a disease started from each of these major airports. (Left) The total monthly traffic of each of those major airports as has been calculated using the world air-traffic data set from September 2017. Each spreading scenario is evaluated over 100 mobility and epidemic realizations.

individuals) to estimate the capacity of airports to spread an infectious disease globally. We seed the disease in each of the world major airports, and simulate the contagion dynamics over a period of two weeks after the outbreak. We rank the airports according to their spreading capacity, as quantified by the TSD of infected individuals (Fig. 2, middle). From this analysis, we observe that total traffic alone cannot predict the power of an airport to spread the disease (comparing left and middle panels in Fig. 2). Total traffic should be accounted for alongside with the location of each spreader airport and the spatial correlations with other influential airports in the network. NRT (Narita International Airport, Tokyo, Japan) and HNL (Honolulu International Airport, Honolulu, USA) airports are indicative examples: while they ranked in the 46th and 117th place by total traffic, respectively, they contribute significantly to the acceleration and expansion of a global disease contagion (ranked by TSD on the 7th and 30th place, respectively). This unexpected phenomenon happens because NRT and HNL combine three important features with high impact on the disease spreading: (1) they have direct connections with the world's biggest mega-hub airports, (2) they operate long-range in- and out-bound international flights, and (3) they are located at geographically conjunctive points between the East and the West (Nicolaides et al., 2012).

The bar plot to the right of Fig. 2 shows the two-week prevalence of the disease, as measured by the percentage of world population that have been affected by the disease two weeks after a disease started from each of the major airports. The two-week prevalence is highly correlated with the total traffic of the airport (the Pearson correlation coefficient is equal to 0.88), indicating that large airports have a big impact in terms of absolute number of affected (infected plus recovered) individuals.

Table II. Reduction of the Disease Impact with a Homogeneous Increase of Hand-Washing Engagement Worldwide

Level of hand cleanliness (@all airports worldwide)	20% (*status quo*)	$X = 30\%$	$X = 40\%$	$X = 50\%$	$X = 60\%$
Rate of hand washing (per hour) (@all airports worldwide)	0.12 (*status quo*)	0.21	0.32	0.49	0.73
Reduction (95% CI) of disease impact (TSD) $(TSD_{20\%} - TSD_X)/TSD_{20\%}$	–	23.7% (21.9–25.5)	43.4% (42.0–44.9)	58.6% (57.6–59.6)	69.1% (68.2–70.0)
Reduction (95% CI) of disease impact (PREV) $(PREV_{20\%} - PREV_X)/PREV_{20\%}$	–	18.2% (17.4–18.9)	33.0% (32.3–33.6)	45.2% (44.6–45.8)	55.4% (54.8–56.0)

Note: These are point estimates and 95% confidence intervals calculated across 120 disease spreading scenarios. In each scenario, the source of the disease is one of the 120 largest airports in the world. Each spreading scenario is evaluated over 100 mobility and epidemic realizations. Throughout these simulations, the following infection-disease–related parameters and hand-washing parameters have been used: $R_0 = 3$, $\mu = 1/4$ days^{-1}, $\beta_1 = R_0 \times \mu = 0.03125$, $\lambda = 0.4$, $\theta = 1/1.5$ hours^{-1}.

3.2. SIR_{WD} Model: Worldwide Homogeneous Hand-Washing Intervention

The effects of hand hygiene are then incorporated in the simulations, and we focus the analysis on the epidemic reaction kinetics as described by the SIR_{WD} model. For each simulation, the disease is seeded at one of the major airports (10 randomly chosen individuals are infected at time $t = 0$), and the geographic epidemic expansion due to the mobility of infected agents is recorded. We first consider the *status quo* scenario, where the hand-cleanliness level is on a 20% steady state at each airport in the world. The rate of hand washing per hour that corresponds to 20% cleanliness is equal to 0.12 hour^{-1} (see Table II). We rank the airports according to the TSD metric, and observe that LHR has the greatest impact while LAX, JFK, SYD, and CDG are among the five most influential spreaders worldwide. Using the same ordering of airports, we repeat the simulations, by increasing the hand-washing engagement rate homogeneously at all airports to achieve global hand-cleanliness levels of 30%, 40%, 50%, and 60%. For each hand-washing engagement rate (or hand-cleanliness level), we analyze the changes in the impact of contagion.

Fig. 3(a) shows the early-time evolution of the fraction of affected individuals over the first two weeks after a disease is seeded at DXB (Dubai Airport). An increase of hand-cleanliness level at all airports from 20% to 60% leads to a significant reduction in the percentage of affected individuals in the total population, from around 1.5% to less than 0.5%. In Fig. 3(b), we demonstrate the spreading power of the most influential spreader airports, as measured by TSD of infected individuals two weeks after a disease was initiated at each of these major airports. We consider several scenarios of homogeneous hand-cleanliness level: 20% (*status quo*), 30%, 40%, 50%, and 60%. A very significant reduction in TSD is observed as the cleanliness level increases, demonstrating that hand hygiene is one of the most important factors to control or even prevent an infection. For example, the spread of an infection seeded in LHR covered about $2.6 \cdot 10^{10}$ square kilometers around the center of mass of the infection within two weeks, while the infected area reduced to less than $1 \cdot 10^{10}$ square kilometers when the cleanliness level increased from 20% to 60% globally. The relative reduction with respect to the *status quo* scenario is calculated as $(TSD_{20\%} - TSD_X)/TSD_{20\%}$ for the TSD metric, or as $(PREV_{20\%} - PREV_X)/PREV_{20\%}$ for the disease prevalence metric, where the cleanliness level, X, increases from 30% to 60% worldwide. Our results indicate a significant reduction of the impact of a disease worldwide, by 24% to 69% as calculated by the TSD, depending on the hand-washing engagement rate worldwide (or by 18% to 55% as calculated by the global prevalence of the disease, Table II).

3.3. The Effect of SIR_{WD} Model Parameters on the Reduction of Global Pandemics due to Hand Washing

We have conducted a comprehensive sensitivity analysis to elucidate the impact of each individual model parameter (hand-washing–related and infectious-disease-related) on the reduction of global pandemics due to hand washing. Throughout this analysis, we consider that the level of hand cleanliness increases from 20% (*status quo*) to 40% at all airports worldwide.

First, we consider the effect of clean hands on the disease infection and its contribution to the

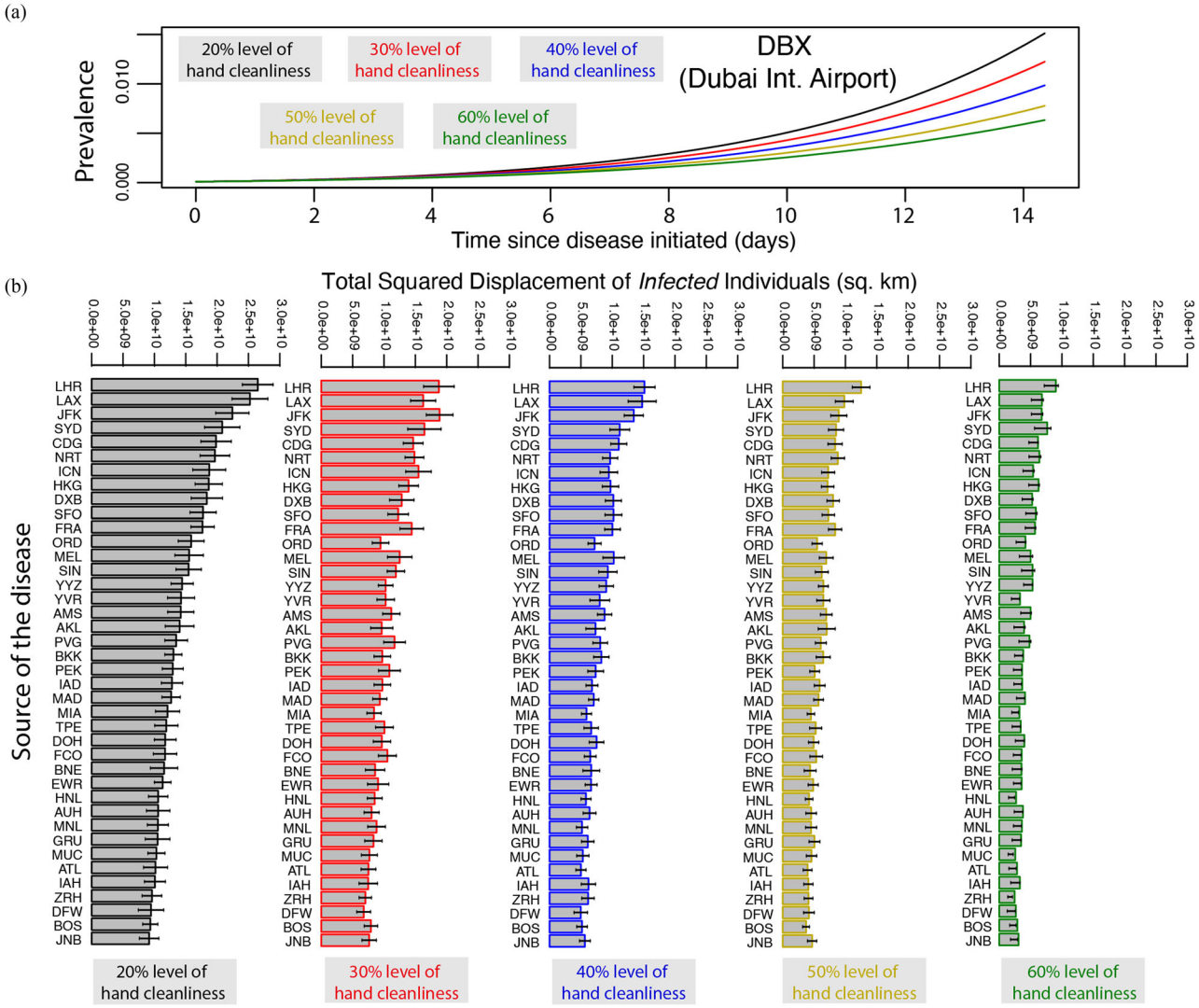

Fig. 3. The effect of a global, homogeneous hand-washing strategy on the impact of a disease spreading. (a) The fraction of affected (infected plus recovered) individuals worldwide over the first two weeks after the infection was initiated at Dubai International Airport at different levels of hand cleanliness. (b) Airports are ranked according to their spreading power to transmit a disease faster and further across globe as measured by the total squared displacement of infected individuals two weeks after a disease started from each individual airport. From left to right the hand-cleanliness level increases from 20% (*status quo*) to 60%. Each spreading scenario is evaluated over 100 mobility and epidemic realizations.

analysis of the global reduction of an infectious disease due to hand-washing interventions. In our model, we have parameterized this effect using λ, which is defined as the percentage reduction of the infection rate of individuals with "clean" hands compared to the infection rate of individuals with "dirty" hands ($\beta_2 = (1-\lambda)\beta_1$). Table III(a) shows the effect of λ on the global reduction of an infectious disease. As expected, for small values of λ ($\beta_2 \approx \beta_1$), the reduction of the global impact of a disease due to hand washing is very small, while for large values of λ ($\beta_2 \ll \beta_1$) the effect of hand washing on disease spreading is significantly larger.

Second, we examine the effect of the hand-washing effectiveness rate—parameterized in our model by θ (θ^{-1}, which is the average time after which an individual with washed hands returns back to the "dirty" state)—on the global reduction of an infectious disease. In Table III(b), we present the results from our simulations for different values

Table III. The Effect of the Two Hand-Washing–Related Parameters (λ and θ) on the Global Reduction of an Infectious Disease

(a) The effect of the reduction of the infection rate parameter due to hand washing λ ($\beta_2 = (1-\lambda)\beta_1$) on the global reduction of an infectious disease[a]

	Percentage Reduction Parameter of Infection Rate Due to Hand Washing (λ)						
Varying Model Parameter	0.7	0.6	0.5	**0.4**	0.3	0.2	0.1
Reduction (95%CI) of disease impact $(TSD_{20\%} - TSD_{40\%})/TSD_{20\%}$	66.6% (65.7–67.6)	59.2% (58.2–60.2)	52.8% (51.6–54.0)	**43.4% (42.0–44.9)**	35.2% (33.6–36.8)	25.0% (23.1–26.8)	11.6% (9.7–13.5)
Reduction (95%CI) of disease impact $(PREV_{20\%} - PREV_{40\%})/PREV_{20\%}$	52.1% (51.4–52.8)	45.3% (44.7–46.0)	39.8% (39.0–40.5)	**33.0% (32.3–33.6)**	25.8% (25.1–26.6)	18.5% (17.7–19.3)	8.3% (7.4–9.2)

(b) The effect of the hand-washing effectiveness rate θ on the global reduction of an infectious disease[b]

	Hand-Washing Effectiveness Rate θ (Hours^{-1})				
Varying Model Parameter	0.5^{-1}	1^{-1}	$\mathbf{1.5^{-1}}$	2^{-1}	2.5^{-1}
Reduction (95%CI) of disease impact $(TSD_{20\%;} - TSD_{40\%;})/TSD_{20\%;}$	33.5% (31.7–35.2)	39.5% (37.9–41.1)	**43.4% (42.0–44.9)**	47.5% (46.2–48.9)	48.1% (46.8–49.5)
Reduction (95%CI) of disease impact $(PREV_{20\%} - PREV_{40\%})/PREV_{20\%}$	24.9% (24.1–25.8)	29.6% (28.8–30.4)	**33.0% (32.3–33.6)**	35.1% (34.4–35.8)	36.7% (36.0–37.4)

Note: Throughout this analysis we consider that the level of hand cleanliness increases from 20% (status-quo) to 40% at all airports worldwide. Highlighted are the results as documented in the main results Table II for the following infection diseases parameters: $R_0 = 3$, $\mu = 1/4$ days^{-1}, $\beta_1 = R_0 \times \mu = 0.03125$, and hand-washing parameters $\lambda = 0.4$, $\theta = 1/1.5$ hours^{-1}. Each spreading scenario is evaluated over 100 mobility and epidemic realizations.

[a]Fixed model parameters: $R_0 = 3$, $\mu = 1/4$ days^{-1}, $\beta_1 = R_0 \times \mu$ and $\theta = 1/1.5$ hours^{-1}.

[b]Fixed model parameters: $R_0 = 3$, $\mu = 1/4$ days^{-1}, $\beta_1 = R_0 \times \mu$ and $\lambda = 0.4$

of the hand-washing effectiveness rate θ. When the average effective persistence of hand washing is large ($\theta^{-1} \sim 2 - 2.5$ hours), the impact of hand washing on the global spread of an infectious disease is larger compared to the case where the effective persistence of hand washing is short ($\theta^{-1} \sim 0.5 - 1$ hour). Both λ and θ^{-1} can take large values with proper hand washing. Therefore, we conclude that proper hand washing can have an important effect on the global spread of touch-transmitted and airborne infectious diseases.

Furthermore, we carry out a sensitivity analysis for the infectious-disease–related parameters (β_1, μ, and R_0) and their impact on our main results and conclusions. Note that the three aforementioned parameters are related by $R_0 = \beta_1/\mu$. Table IV(a) shows the simultaneous sensitivity of the disease recovery rate, μ, and infection rate, β_1—keeping the basic reproductive number, R_0, constant—on the global reduction of an infection due to hand-washing intervention. In these simulations we vary the recovery rate from $\mu = 1/3$ to $1/5$ days^{-1} in 0.5-day increments. The infection rate, β_1, changes accordingly, so that the basic reproductive number, R_0, remains constant and equal to 3. From the results presented in Table IV(a), we observe that as the average effective duration of a disease, μ^{-1}, increases from three to five days (and therefore the infection rate decreases from $\beta_1 = 0.042$ to $\beta_1 = 0.025$ keeping the reproductive number, R_0, constant), the reduction of the global infection impact due to hand washing, as measured by the TSD, decreases slightly from 48.1% to 40.65% (from 37% to 29.5% as measured by the global prevalence of the disease). In Table IV(b), we present the simultaneous sensitivity of the disease recovery rate, μ, and basic reproductive number, R_0—keeping the infection rate, β_1, constant—on the global reduction of an infection due to hand-washing intervention. When the average effective duration of a disease, μ^{-1}, increases from three to five days (and therefore the basic reproductive number increases from $R_0 = 2.25$ to $R_0 = 3.75$ in order to keep, β_1, constant), the reduction of the global infection impact due to hand washing measured by the TSD changes from 47.7% to 41.4% (33.4% to 32.2% when measured by the global prevalence of the disease).

Similar conclusions may be derived from Table IV(c), which presents the simultaneous

Table IV. The Effect of the Infectious-Disease–Related Parameters (β_1, μ, and R_0) on the Global Reduction of an Infectious Disease Due to Hand Washing

(a) The effect of the infection recovery rate μ (keeping the reproductive number R_0 constant) on the global reduction of an infectious disease due to hand washing[a]

	Recovery Rate μ(days^{-1})/Infection Rate β_1				
Varying Model Parameter	3^{-1}/0.042	3.5^{-1}/0.036	**4^{-1}/0.031**	4.5^{-1}/0.028	5^{-1}/0.025
Reduction (95%CI) of disease impact (TSD) $(TSD_{20\%} - TSD_{40\%})/TSD_{20\%}$	48.1% (46.8–49.5)	46.3% (44.5–47.6)	**43.4% (42.0–44.9)**	42.5% (41.0–44.0)	40.65% (39.0–42.3)
Reduction (95%CI) of disease impact (PREV) $(PREV_{20\%} - PREV_{40\%})/PREV_{20\%}$	36.9% (36.0–37.8)	35.0% (34.3–35.7)	**33.0% (32.3–33.6)**	30.9% (30.2–31.6)	29.5% (28.8–30.2)

(b) The effect of the recovery rate μ (keeping the infection rate β_1 constant at he global reduction of an infectious disease due to hand washing[b]

	Recovery Rate μ (days^{-1})/Reproductive Number R_0				
Varying Model Parameter	3^{-1}/2.25	3.5^{-1}/2.63	**4^{-1}/3**	4.5^{-1}/3.37	5^{-1}/3.75
Reduction (95%CI) of disease impact (TSD) $(TSD_{20\%} - TSD_{40\%})/TSD_{20\%}$	47.7% (45.9–49.5)	45.2% (43.6–46.9)	**43.4% (42.0–44.9)**	44.4% (43.0–45.7)	41.4% (40.1–42.8)
Reduction (95%CI) of disease impact (PREV) $(PREV_{20\%} - PREV_{40\%})/PREV_{20\%}$	33.4% (32.5–34.2)	32.5% (31.7–33.3)	**33.0% (32.3–33.6)**	32.9% (32.1–33.6)	32.2% (31.5–32.8)

(c) The effect of the infection rate β_1 (keeping the recovery rate μ constant) on the global reduction of an infectious disease due to hand washing[c]

	Infection Rate β_1/Reproductive Number R_0				
Varying Model Parameter	0.02/1.92	0.025/2.4	**0.031/3**	0.035/3.36	0.04/3.84
Reduction (95%CI) of disease impact (TSD) $(TSD_{20\%} - TSD_{40\%})/TSD_{20\%}$	38.8% (36.3–41.4)	40.2% (38.2–42.1)	**43.4% (42.0–44.9)**	44.4% (43.3–45.7)	44.8% (43.7–45.9)
Reduction (95%CI) of disease impact (PREV) $(PREV_{20\%} - PREV_{40\%})/PREV_{20\%}$	25.8% (25.0–26.7)	29.4% (28.6–30.3)	**33.0% (32.3–33.6)**	34.3% (33.7–35)	35.5% (34.7–36.2)

Note: Throughout this *sensitivity analysis* we consider that the level of hand cleanliness increases from 20% (status-quo) to 40% at all airports worldwide. Highlighted are the results as documented in the main results Table II for the following infection diseases parameters: $R_0 = 3$, $\mu = 1/4$ days^{-1}, $\beta_1 = R_0 \times \mu = 0.03125$, and hand-washing parameters $\lambda = 0.4$, $\theta = 1/1.5$ hours^{-1}. Each spreading scenario is evaluated over 100 mobility and epidemic realizations.

[a]Fixed model parameters: $R_0 = 3$, $\lambda = 0.4$ and $\theta = 1/1.5$ hours^{-1}.

[b]Fixed model parameters: $\beta_1 = 0.03125$, $\lambda = 0.4$ and $\theta = 1/1.5$ hours^{-1}.

[c]Fixed model parameters: $\mu = 1/4$ days^{-1}, $\lambda = 0.4$ and $\theta = 1/1.5$ hours^{-1}.

sensitivity of the infection rate, β_1, and basic reproductive number, R_0— keeping the recovery rate, μ, constant—on the global reduction of an infection due to hand-washing intervention. We observe that, as β_1 increases (and therefore R_0 increases to keep μ constant), the relative reduction of the global infection impact due to hand washing measured by the TSD or PREV increases slightly, showing that hand washing may be slightly more effective in the case of more aggressive infectious diseases.

The above analysis suggests that small changes in the infectious-diseases–related parameters (β_1, μ, and R_0) do not have a significant effect on the global reduction of infection impact due to hand washing, rendering our conclusions robust with respect to disease type as measured by combinations of the above epidemiological parameters. In contrast, hand-washing–related parameters have a significant effect on the results, perhaps as expected (Table III).

3.4. SIR_{WD} Model: Strategic Hand-Washing Policies

Since increasing the level of hand-washing engagement homogeneously at all airports is very

costly, and maybe infeasible, we simulate some other less-costly scenarios. These scenarios consider the increase of the hand-washing engagement rate only at a small number of "key" airports. We test three intervention scenarios that implement the increase of hand-washing engagement rate at: (i) the 10 key airports worldwide, (ii) the 10 key airports of each source of the disease, and (iii) only at the source of the disease.

For the intervention scenario (i), we preidentify the 10 key airports of the world air-transportation network by multiplying the susceptibility of each airport by the strength of the airport to spread an infection globally. The strength of each airport i is calculated as $s_i = T_i k_i \sum_{i=1}^{k_i} w_{ij} d_{ij}$, where T_i is the total outgoing traffic from i, k_i is the number of connections of i (i.e., the degree of node i in the network), and $\sum_{i=1}^{k_i} w_{ij} d_{ij}$ is the effective length of all links of i, which is the weighted sum of the actual distances d_{ij} between i and j nodes. The weights w_{ij} are the fractions of passengers traveling from i to j. The susceptibility of airport i is calculated using the simulations of the conventional SIR model, as the weighted average fraction of infected individuals that arrive at i over all the seeding scenarios considered in the SIR model described in Section 2. Using the above combined metric (susceptibility $\times$ strength), we identify the 10 key airports of the global air-transportation network as being the LHR, LAX, JFK, CDG, DXB, FRA, HKG, PEK, SFO, and AMS. For the intervention scenario (ii), we identify 10 key airports for each source of the disease, by multiplying the airport strength with the source-dependent susceptibility. The source-dependent susceptibility of airport i from the source of the infection airport j, is calculated as the fraction of infected individuals that arrive at i from j. For this intervention scenario, prior knowledge of the source of the disease is required and for different sources of the disease, we have different sets of key airports (see Fig. 4). Finally, for the intervention scenario (iii), since we increase the hand-washing engagement rate only at the source of the disease, prior knowledge of the source is required.

Our results indicate that the design of a less costly (compared to homogeneous) strategic plan for hand-washing intervention only at 10 preidentified key airports worldwide (Scenario (i)) could lead to a significant reduction of the disease impact calculated by the TSD from $\sim 8\%$ to $\sim 37\%$ (or $\sim 7\%$ to $\sim 29\%$ calculated by the disease prevalence, Fig. 4). If the strategic plan is deliberately implemented only at the 10 most important airports for each source of disease (Scenario (ii)), we observe a further reduction of the disease impact. However, this further reduction is statistically different from that of Scenario (i) only in terms of the prevalence of the disease, but not in terms of geographical spreading, as calculated through the TSD metric. Intervention Scenario (iii), which considers enhancing hand-washing engagement only at the source of the disease, has a significant effect on the reduction of disease impact; yet, this effect is smaller than that of intervention Scenarios (i) and (ii).

4. DISCUSSION

In this work, we analyze contagion dynamics through the world air-transportation network, and the impact of hand-hygiene behavioral changes of air travelers against global epidemic spreading. Using well-established methodologies, we apply simulations to track traveling agents and their hand-washing activity and analyze the expansion of flu-type epidemics through the world air-transportation network. Using Monte Carlo simulation, we measure the early-time spreading power of the major airports in the world under different hand-hygiene interventions.

Our data-driven analysis shows that at most one over five people have "clean" hands at any given moment in time (i.e., 20% of airport population). Our simulation results suggests that, if we were able to increase the level of hand cleanliness at all airports in the world from 20% to 30%, either by increasing the capacity of hand washing and/or by increasing awareness (Funk, Gilad, Watkins, & Jansen, 2009) among individuals and/or by giving the right incentives to individuals, a potential infectious disease would have a worldwide impact that is about 24% smaller compared to the impact that the same disease would have with the 20% level of hand cleanliness. Increasing the level of hand cleanliness to 60% at all airports in the world would have a reduction of 69% in the impact of a potential disease spreading. We investigate how those results change for different hand-washing model parameters and we perform sensitivity analysis of the epidemiological model parameters showing that our results are quite robust with respect to the infectiousness of the disease.

Moreover, we design and evaluate a less costly (compared to homogeneous) strategic plan for hand washing at a small number of locations. Under this intervention scenario, our simulations identify the 10

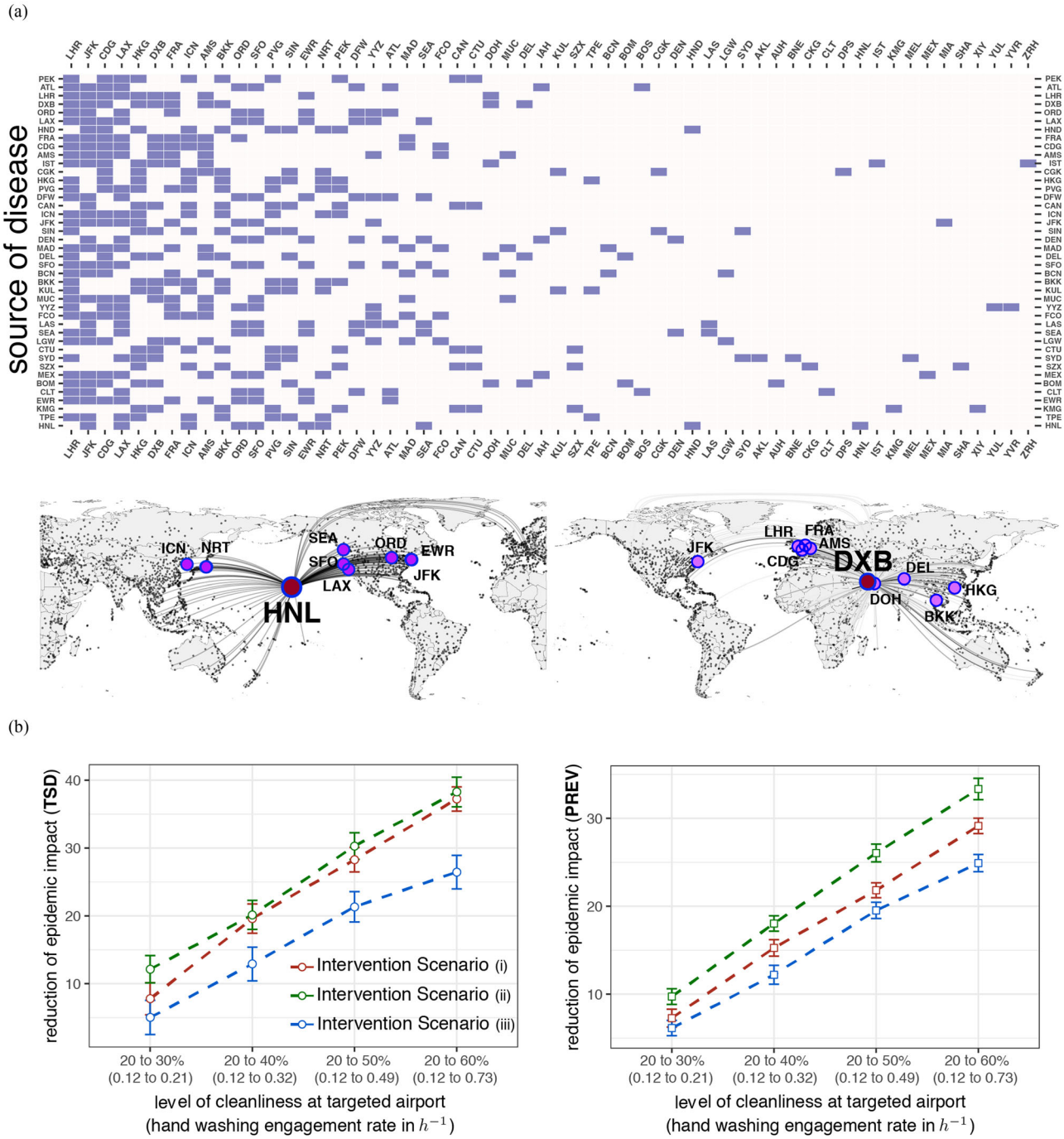

Fig. 4. The effect of strategic hand-washing policies on the impact of disease spreading. (a) The 10 key airports of each source of disease. When the disease is seeded in each of the source (in this plot we show as source the 42 busiest airports of the network), we increase the hand-washing engagement rate at the 10 key airports in relation to each source for scenario (ii) of our simulations and analyze the early-time contagious dynamics. (Lower) The locations of the 10 important airports for HNL—Honolulu International Airport (left) and for DXB—Dubai International Airport (right) shown in the global map. (b) Reduction of the disease impact as a function of the level of hand cleanliness (or hand-washing engagement rate) with respect to *status quo* for the three different intervention strategies (scenarios). Disease impact is calculated with respect to the Total Square Displacement (TSD) at the left and the Prevalence of the disease (PREV) at the right. These are point estimates and 95% confidence intervals across 120 disease spreading scenarios. In each spreading scenario, the source of the disease is one of the 120 largest airports in the world. Each spreading scenario is evaluated over 100 mobility and epidemic realizations.

most important airports of the network, for which increasing the level of hand cleanliness (or hand-washing engagement rate) only at those, the impact of the disease spreading would decrease by 8% to 37%.

Our current approach has some limitations. First, we use the simple SIR reaction kinetics model, while a more complicated model like the SEIR (where E denotes the Exposed compartment) could provide inferences on the impact of hand-washing behavior among the individuals exposed to the disease on the expansion of epidemics. Second, at each location we consider a closed, homogeneous population, where each individual may come in close contact with any other individual with the same probability. In other words, we assume homogeneous population mixing within each subpopulation. Of course, in reality, the pattern of contacts among individuals within a population is not random but quite heterogeneous. While we believe that heterogeneity in long-range mobility patterns (that we take well into account using real-world human travel data) dominates the effect of the heterogeneity of contacts within subpopulations on the global spread of infectious diseases, future research may focus on elucidating the impact of those local-scale contact patterns. A third limitation is the assumption of a homogeneous hand-hygiene behavior of air travelers, as we do not know the actual hand-washing activity that varies among individuals within a local population and among individuals from different societies and cultures. Observational studies on human personal-hygiene habits can provide an understanding on hand-washing–related behavior and insights on how social interventions can change it.

Epidemiological outbreaks not only increase global mortality rates, but also have a large socioeconomic impact that is not limited to those countries that are directly affected by the epidemic. Outbreaks reduce the consumption of goods and services, negatively affecting the tourism industry, increasing businesses' operating costs, and speeding the flight of foreign capital, generating massive economic costs globally. For instance, even the relatively short-lived SARS epidemic in 2003 led to the cancellation of numerous flights and to the closure of schools, wreaking havoc in Asian financial markets and ultimately costing the world economy more than $30 billion (Smith, 2006). Hypothetical scenarios of future global pandemics give estimates on the economic effects. The worldwide spread of a severe infectious disease is estimated to cause approximately 720,000 deaths per year and an annual reduction of economic outcome of $500 billion (i.e., $\sim 0.6\%$ of the global income) (Fan, Jamison, & Summers, 2018). In such severe scenarios where markets shut down entirely, a massive global economic slowdown is expected to occur shrinking the GDP of national economies. Of course, wealth and income effects are expected to differ sharply across countries, with a major shift of global capital from the affected economies (i.e., of developing countries) to the less-affected economies (i.e., of North America and Europe).

The effectiveness of mitigation strategies against global pandemics is evaluated through the total expected cost versus the total public health benefit (Chung, 2015). The target of each strategy is to maximize the social welfare by incurring in the minimum economic cost. For interventions where travel restrictions are implemented (Ferguson et al., 2006), the cost increases with the number of closed airports and the number of individuals that get stranded in those airports. The reward is related to the relative decrease in the global footprint of the disease, compared with the null case of noninterventions. In contrast to the mobility-driven strategies that change the population mobility patterns, other solutions such as hand washing appear to be more cost- and reward-effective. A future research on the socioeconomic impact of global pandemics and the cost-effectiveness ratio of different mitigation strategies (e.g., hand washing, vaccination, airport closures, mobility routing diversions) against disease spreading would evaluate the efficiency and significance of hand-hygiene interventions. However, while hand hygiene is considered as the first prevention step in the case of an epidemic emergency, the capacity of hand-washing facilities in crowded places including airports, is limited only to wash basins at restrooms. It is not known, however, if increased capacity would enhance hand-washing engagement by air travelers. New technology is being developed aiming to increase the capacity of facilities even outside restrooms, thus expanding the options for hand hygiene and the solutions for air and surface sterilization. Airbus (2018), for example, is exploring an innovative antimicrobial technology that is able to eliminate viruses and pathogens from aircraft surfaces (e.g., tray tables, seat covers, touch screens, galley areas). Boeing is also exploring a prototype self-sanitizing lavatory that uses ultraviolet light to kill 99.99% of pathogens (Boeing, 2016). At the same time, robotic systems for dirt detection and autonomous cleaning of contaminated

surfaces (Bormann, Weisshardt, Arbeiter, & Fischer, 2013) and smart touch-free hand-washing systems (Smixin, 2017) are promising tools on the evolution of cleaning technologies.

An important question is how such smart hand-washing technologies will be adopted by the general public, and what incentives can promote hand-washing behavioral changes. Do digital nudges (motivation messages) make health-related establishments attractive to individuals? A recent study has found that nudges have been effective at improving outcomes in a variety of health-care settings including a significant increase of influenza vaccination rates (Patel, 2018). Can social influence or peer effects improve hand-washing engagement? Recent works have identified that social influence plays an important role in many behaviors like exercise or diet (Aral & Nicolaides, 2017; Lim & Meer, 2018), and there is some initial evidence that it can play a role in individual hygiene (Grover et al., 2018). There is certainly a need for rigorous and carefully designed field experiments on a large population scale, to identify and measure the causal effect of digital nudges, incentives, and peer influence on public hand-washing engagement of air travelers as well as the mechanisms of health-enhancing human behavior change.

The current research can potentially shape the way policymakers design and implement strategic interventions based on promoting hand washing in airports, which could help hindering any infection within a confined geographical area during the early days of an outbreak, inhibiting its expansion as a pandemic. Our study concludes that population engagement with proper hand hygiene could be a simple and effective solution for preventing transmission of infections and reducing the risk of massive global pandemics. This should be followed up by the design of mechanisms that enable improvements with respect to the capacity of hand-washing facilities in public places, and different interventions that will enhance the adoption of hand-hygiene–related behaviors.

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