The effect of an emergency evacuation on the spread of COVID19

Sachit Butail[1*], Maurizio Porfiri[2,3,4*]

[1]Department of Mechanical Engineering, Northern Illinois University, DeKalb, IL, USA

[2]Department of Mechanical and Aerospace Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA

[3]Department of Biomedical Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA

[4]Department of Civil and Urban Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA

***Correspondence:**
Sachit Butail
sbutail@niu.edu

Maurizio Porfiri
mporfiri@nyu.edu

Keywords: COVID19, evacuation, aerosol, crowds, proximity.

Abstract

In an emergency evacuation, people almost always come in close proximity as they force themselves to leave a built environment under a potential threat. With COVID19, this situation presents yet another challenge: that of getting unintentionally exposed to an infected individual. To assess the epidemiological consequences of an emergency evacuation, we expanded on a popular pedestrian dynamic model to enable social distancing during a normal exit and analyze transmission through respiratory droplets and aerosol. Computer simulations point to a troubling outcome, whereby the benefits of a quick exit could be outweighed by the risk of infection.

1 Introduction

As schools and universities continue to evaluate various social distancing strategies to mitigate the spread of COVID19, a critical feature of human behavior is being overlooked—the response to a sudden alarm in a built environment that may trigger an emergency evacuation. The alarm may come from a fire in the building, the presence of an active shooter, or even a simple drill to prepare for true emergencies. Perhaps, in the current context, even someone blatantly unwilling to comply with social distancing regulations and use of masks could trigger an alarm. Whatever the source of the alarm, during an evacuation, individuals will likely weigh the risks of being injured from the perceived threat heavily against the possibility of contracting an infection from a classmate or the instructor. Upon exiting however, people may wonder if they got too close to an infected person and if they breathed the same air for too long. These aspects represent an important discussion in relation to airborne transmission of COVID19[1,2].

The recommended separation distance of two meters (six feet) is largely based on the transport of "respiratory droplets produced when an infected person coughs, sneezes, or talks."[2] These droplets can be propelled through air for up to two meters and "land in the mouths or noses of people who are nearby or possibly be inhaled into the lungs."[2] More recently, results from fluid mechanics research have shown that aerosol could be the dominant driving mechanism for transmission between people in close proximity[3]. In comparison with respiratory droplets, aerosol includes much smaller particles that remain suspended in air for long periods of time to be inhaled by others. Irrespective of the driving mechanism, close physical presence of an infected individual is likely to increase the risk of infection, especially in the event of screaming.

2 Risk of infection from an individual as a function of their physical proximity

Under the premise that the risk of an infection increases with the proximity to an infected individual, we could quantify the epidemiological consequences of an evacuation by tracking the separation distance within the crowd. More specifically, we measure the risk of exposure in a crowd of N people from an infected individual I as $E = \max_{j \neq I} \int_t e^{-\tau d_{Ij}(t)} dt$, where $d_{Ij}(t)$ is the instantaneous distance between individual I and any other individual in the crowd, and τ is the spatial decay rate of the transmission. The maximization ensures that we select the individual who receives the highest exposure within the crowd and quantifies the risk in terms of a worst-case scenario. The higher the value of E is, the more likely the infected individual will create a new infection in the crowd. This definition is agnostic to the specific mechanism of transmission, be it respiratory droplets or aerosol, and allow for a direct comparison among feasible scenarios.

An estimate of the value of τ can be obtained through a linear regression of the plots in logarithmic scale presented in Figure 7 of Chen et al.[3]. These plots include exposure from both talking and coughing for droplets of size more than 100 μM (respiratory droplets) and short-range airborne (aerosol) as functions of distance. Hence, we obtain the following estimates: talking/respiratory droplets: $\tau = 16.29\ \mathrm{m}^{-1}$; talking/aerosol: $\tau = 9.46\ \mathrm{m}^{-1}$; coughing/respiratory droplets: $\tau = 7.64\ \mathrm{m}^{-1}$; and coughing/aerosol: $\tau = 5.29\ \mathrm{m}^{-1}$. As a reference for values of E that could lead to an infection, we can follow guidelines of the Centers for Disease Control and Prevention (CDC)[9] that define a "close contact" as one that may trigger an infection by being within two meters of an infected individual for more than 15 minutes. By considering the most extreme case of aerosol transmission during coughing, the value of E that corresponds to close contact is 2.29×10^{-2} s. This value can be used as a simple threshold to assess a close contact in a crowd.

3 Simulating emergency evacuations and normal exit with social distancing

Emergency evacuations represent a dire situation where people exit a built environment as quickly as possible to escape the perceived danger. In an evacuation, the resulting crowd dynamics arise from a complex interplay between psychological, social, and physical factors. Individuals use social, cognitive, visual, and physical cues to stay with friends and family[4], look for the exit[5], and avoid collisions and injury[6]. Evacuation is therefore a cognitively demanding situation, which makes it inevitable for individuals to come close to each other—much less than the stipulated two-meter distance. Could this increase the risk of contracting COVID19?

Experiments on evacuation are impractical and potentially dangerous to conduct. A number of agent-based, mathematical models have been proposed over the years to predict human response and support hypothesis-driven experiments to clarify the mechanisms of the crowd dynamics. Among those, the social force model[7] constitutes a viable compromise between model complexity and predictive power. The social force model is a physics-based model that captures interactions between finite-sized particles (agents) in the form of four kinds of forces: a social force that keeps agents apart; a goal force that makes them orient and move towards a goal location; a physical force in the event of friction and collision between agents; and a wall force, which is the same as the social force but captures interaction with walls and obstacles instead of other agents. Computer simulations can reproduce several real-world phenomena, including occurrences of bottlenecks near exits, injuries during an evacuation of a large crowd, and lane formation in corridors. The social force model has been validated in laboratory experiments[8], as well as real-world scenarios[6], thereby constituting a valid framework for exploring the potential epidemiological implications of an evacuation. By combining the classical evacuation model from Helbing et al.[7] with the proposed definition of risk of exposure, it is possible to provide a first assessment of the epidemiological consequences of an evacuation, compared to a normal exit where people can exercise social distancing.

The social force model[7] captures the motion of agent i as the combination of three effects, a desire to move towards the exit goal, maintain separation from others, and maintain distance from walls. This is mathematically written as $m\ddot{\boldsymbol{x}}_i = \boldsymbol{f}_g + \sum_j \boldsymbol{f}_{ij} + \sum_W \boldsymbol{f}_{iW}$, where m is the common mass of each agent (80 kg), $\boldsymbol{x}_i$ is the two-dimensional position vector of agent i, $\boldsymbol{f}_g$ is the goal force, $\boldsymbol{f}_{ij}$ includes the social force and the physical force between agents i and j, and $\boldsymbol{f}_{iW}$ is the wall interaction force for agent i with respect to the wall W. The goal force is modeled as $\boldsymbol{f}_g = \frac{v_0\boldsymbol{e}-\boldsymbol{v}}{\alpha}$, where v_0 is the desired speed that encapsulates the urgency with which the agent must leave the built environment, $\boldsymbol{e}$ is the direction towards the exit, $\boldsymbol{v}$ is the instantaneous velocity, and $\alpha = 0.5$ s is the relaxation time. The interaction force is $\boldsymbol{f}_{ij} = \left\{Ae^{\frac{(r_{ij}-d_{ij})}{B}} + kg(r_{ij} - d_{ij})\right\}\boldsymbol{n}_{ij} + \kappa g(r_{ij} - d_{ij})\Delta v_{ji}\boldsymbol{t}_{ij}$, where r_{ij} is the sum of the radii of agents i and j (modeled as circles); d_{ij} is the distance between agents i and j ; $\boldsymbol{n}_{ij}$ identifies the direction from j to i, and $\boldsymbol{t}_{ij}$ denotes the direction that is perpendicular to $\boldsymbol{n}_{ij}$; A and B are constants that determine the strength of social interaction, with higher values leading to larger distances between agents; and $k = 1.2 \times 10^5$ kg s^{-2} and $\kappa = 2.4 \times 10^5$ kg m^{-1}s^{-1} determine the strength of physical interaction and friction effects, with the function g being equal to $r_{ij} - d_{ij}$ if $r_{ij} > d_{ij}$ and is zero otherwise. The wall interaction force $\boldsymbol{f}_{iW}$ has the same form of the social interaction force, so that an agent stays away from the wall and experiences physical force when in contact.

To quantify and compare the risk associated with an emergency evacuation, we simulated two scenarios: evacuation and normal exit with social distancing. To simulate these two scenarios, we varied the interaction range (parameter B in the model), interaction repulsive force (parameter A in the model), and desired speed (parameter v_o in the model) within the social force model (Fig. 1). For a normal exit where people exercise social distancing (Fig. 1A), we set a large interaction range and a strong interaction repulsive force, along with a low desired speed of 1 m/s. On the other hand, for an evacuation, we utilize a low interaction range and a weak repulsive force (Fig. 1B), accompanied by a high desired speed of 5 m/s. The selection of these desired speeds reflect walking and running speeds during normal and emergency situations[7].

Specifically, evacuation was simulated by setting $A = 20$ kN, $B = 0.08$ m, $v_0 = 5$ m s^{-1}, which were the default values proposed in Helbing et al.[7] to simulate an evacuation; the A and B parameter values for exit with social distancing were selected by simulating exit scenarios with a range of values $A \in \{20, 40, 60, \dots, 200\}$ kN, $B = \{0.08, 0.16, 0.24, \dots, 0.72\}$ m, for a normal walking speed of $v_0 = 1$ m s^{-1} and calculating the average distance to the nearest neighbor for all agents in the room for the first ten seconds; we found that the average distance to nearest neighbor increased steadily with A and B before it plateaued at approximately 1.7 m due to the wall and room size constraints. We selected $A = 10$ kN, and $B = 0.48$ m at which the agents remained as far apart as possible while not exhibiting unnatural jitter associated with amplified forces from the walls. All other parameter values were kept the same as set in the open source code provided as part of Helbing et al[7]. Simulations were performed using the C source code provided as Supplement to the paper by Helbing et al.[7]

To prevent goal and interaction forces from balancing out to an equilibrium for the exit with social distancing scenario, the goal force was multiplied by a factor k_g that was a function of the distance to the exit d_e.This distance-dependent factor was set to an exponentially decaying value, namely, $k_g = 1 + C_1 \exp(-C_2 d_e)$, with $C_1 = 100$, and $C_2 = 1\ \text{m}^{-1}$ so that agents felt a stronger pull towards the exit as they got closer to it.

For each simulation, we randomly placed 25 agents (modeled as finite-sized circles) within a 10 × 10 m room with a single 1 m wide exit; this number of individuals is sufficiently low to allow for maintaining a separation distance of two meters within the room. Randomness in the simulation was introduced through two means: first, ten simulations were performed in each scenario, where each simulation corresponded to a different initial condition and the distribution of agent size (circles with diameters ranging uniformly between 0.5 and 0.7 m), and, second, by selecting a different agent as the single infected agent within the crowd. This amounted to hundred different realizations of each scenario. The risk of exposure, E, was computed for each scenario for different values of τ.

Figure 1C shows that the exposure for an agent within the evacuating crowd without social distancing is much larger than when the crowd leaves normally and maintains social distance, despite the evacuating crowd leaves the arena much sooner than a crowd that normally exits and maintains social distance (Fig. 1E). Figure 1D confirms that the agents maintain larger distances as a result of the higher interaction range and repulsive force encoded into the model.

4 Discussion

Despite the evacuating crowd takes only a sixth of the time to leave the room than when the crowd which is exiting normally, evacuation presents a far greater threat for possible transmission of COVID19. For example, in the case of aerosol transmission, evacuating in the presence of an infected individual who is coughing will yield a risk of exposure due to aerosol transmission of about 0.1 s (above the estimate of the threshold of close contact), while exit with social distancing will cause an average exposure ten time smaller (below the estimate of the threshold of close contact).

A vast community of researchers is focused on understanding how the flow of individuals during an emergency evacuation can be eased to avoid bottlenecks and high pressures that could lead to injuries and fatalities[10]. COVID19 presents yet another complication, where we must also weigh our compulsion to run away from a potential threat against the possible risks involved in being in proximity to an infected individual. Our results indicate that maintaining social distancing during an exit could increase the time required to leave the built environment by a factor of ten, which may be fatal in the case of a fire or a mass shooting. At the same time, evacuating without maintaining a social distance dramatically increases the risk of exposure, potentially leading to further infections. Face coverings can certainly help mitigate these risks, although more research is required to precisely evaluate the reduction in the decay rate associated with the proper use of masks, especially in the context of aerosol intake. Overall, this study points to a critical gap in the current guidelines for resuming in-presence learning, as well as opening up businesses during the coming fall.

Our analysis is not free of limitations, which should be investigated in further efforts, beyond the scope of this perspective. First of all, the pedestrian dynamics is described by one of the very first mathematical models in the field[7], which has seen several refinements throughout the last twenty years[11]. As such, one may attempt at more complex simulation of the evacuation process to capture perceptual and psychological factors that are missing in this model. Second, the contact process examined herein does not account for individual orientation, which is likely to play an important role on droplet-based exposure, and, to a lesser extent, on airborne transmission[3]. This limitation for example could be overcome by following the approach proposed by Ronchi & Lovreglio[12] to combine risks of infections across a range of viable scenarios in a built environment. Overall, this study contributes to the general topic of safety-related issues during the current pandemic[13], by bringing forward preliminary evidence for the expected risks of infection during evacuations.

5 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

6 Author Contributions

Both S.B and M.P. designed the study, performed the study, discussed the results, and wrote the manuscript.

7 Funding

S.B. was supported by the National Science Foundation, under grant # CMMI-2027988, and M.P. was supported by the National Science Foundation, under grant # CMMI-2027990.

8 Data Availability Statement

The code and datasets used for analysis in this study can be found in https://www.dropbox.com/sh/xfyla1trzay458f/AAC2cWEVNgH-aIIN4vh-5COta?dl=0

9 References

1. Morawska, L., Tang, J. W., Bahnfleth, W., Bluyssen, P. M., et al. (2020). How can airborne transmission of COVID-19 indoors be minimised?. Environment international, 142, 105832.
2. Centers for Disease Control and Prevention (CDC) (2020), How to Protect Yourself & Others, https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html
3. Chen W., Zhang N., Wei J., Yen H.L., Li Y. (2020) Short-range airborne route dominates exposure of respiratory infection during close contact. Build Environ 176:106859
4. Mawson A.R. (2017) Mass panic and social attachment: The Dynamics of Human Behavior. Routledge London
5. Moussaïd M., Helbing D., Theraulaz G. (2011) How simple rules determine pedestrian behavior and crowd disasters, Proc Natl Acad Sci U S A. 108(17):6884-6888
6. Helbing D., Buzna L., Johansson A., Werner T. (2005) Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. Transp Sci 39(1):1-24
7. Helbing D., Farkas I., Vicsek T. (2000) Simulating dynamical features of escape panic. Nature 407: 487-490

8. Moussaïd M., Helbing D., Garnier S., Johansson A., Combe M., Theraulaz G. (2009) Experimental study of the behavioural mechanisms underlying self-organization in human crowds. Proc Biol Sci 276(1668): 2755-2762
9. Centers for Disease Control and Prevention (CDC), (2020) When to Quarantine, https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/quarantine.html
10. Schadschneider A., Klingsch W., Klüpfel H., Kretz T., Rogsch C., Seyfried A. (2009) Evacuation Dynamics: Empirical Results, Modeling and Applications In: Meyers R (ed) Encyclopedia of Complexity and Systems Science Springer, New York
11. Martinez-Gil, F., Lozano, M., García-Fernández, I., Fernández, F. (2017). Modeling, evaluation, and scale on artificial pedestrians: a literature review. ACM Computing Surveys (CSUR), 50(5), 1-35.
12. Ronchi, E., Lovreglio, R. (2020). EXPOSED: An occupant exposure model for confined spaces to retrofit crowd models during a pandemic. arXiv preprint arXiv:2005.04007.
13. Haghani, M., Bliemer, M. C., Goerlandt, F., Li, J. (2020). The scientific literature on Coronaviruses, COVID-19 and its associated safety-related research dimensions: A scientometric analysis and scoping review. Safety Science, 104806.

10 Figure captions

Figure 1: The epidemiological risks from coming close to an individual during an evacuation could outweigh the benefits of being able to quickly leave a room under a potential threat. (**A**), (**B**), Snapshots from a simulation of the pedestrian evacuation model[7] as 25 agents exit a 10×10 m room through a one-meter wide door while maintaining social distance or evacuate without maintaining social distance. (**C**), Risk of exposure of an individual in the crowd as a function of the decay rate of the transmission; a low value of τ indicates high transmission at larger separation distances (red denotes evacuating, and turquoise identifies exiting and social distancing). (**D**), Average distance to the nearest neighbor during the two types of simulations performed (red denotes evacuation without distancing, and turquoise identifies exiting with distancing). (**E**), Leaving time for more than ninety percent of the crowd for the two scenarios.