Using Agent-Based Modelling to Understand Advantageous Behaviours Against COVID-19 Transmission in the Built Environment

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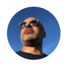

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Using agent-based modelling to understand advantageous behaviours against COVID-19 transmission in the built environment

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Abstract. The global Covid-19 pandemic has raised many questions about how we occupy and move about in the built environment. Interior environments have been increasingly discussed in numerous studies highlighting how interior spaces play a key key in the spread of pandemics, especially in winter months when people spend most of their time in closed spaces. In the coming years, one societal challenge will be to find short-term strategies to reopen indoor venues. Most current approaches focus on an individual's behavior (maintaining social dis- tance, wearing face masks, and washing their hands) and government policies (confinement, curfew, quarantine, etc.). However, few studies have been conducted to understand a building's interior where most transmission takes place. The impact of the architectural space on the health of occupants is increasingly present in research. One question that arises is: how will the utilization of existing interior spaces be improved above and beyond universally applied criteria, while minimizing the risk of disease transmission? This article presents an agent-based model that explores this question. This model examines disease transmission in various "interior types" in combination with user behaviors and their mobility, as well as three types of transmission vectors (direct, airborne and via surfaces), to highlight risk. The model also integrates numerous policy interventions, including wearing masks and hand washing, and the possibility of easily modifying the organization of spaces. Different studies at various scales were conducted both on the University of Guadalajara (UdeG) campus as well as at the MIT Media Lab were to illustrate the application of this model.

1 Introduction

1.1 Context

The Covid-19 pandemic has caused great disruption in higher education institutions. Colleges and universities around the world have had to suspend face-to-face activities for virtual learning and communication to prevent virus transmission. Institutional coordination challenges dramatically increased when considering the process of reintroducing in person learning both during and post pandemic. To support decision making vis-a-vis reoccupying spaces, simulation models have been developed to accompany and understand the impact of reopening policies. In addition we explored scientific observations and statements and policies from global experts (e.g OECD [1] and (WHO) [2]) regarding health measures applied to school contexts are explored in this paper. The objective is for academic institutions to generate the appropriate conditions for their facilities and promote responsible and preventive behaviors for a responsible return with minimum risk.

1.2 Approach

In the context of the Covid-19 pandemic, setting up experiments with real people to test different interventions poses too high a risk for participants. To overcome this challenge, computer models can be used as a tool to explore different strategies in a virtual environment, so called in silico, before implementation [3]. Strategies for mitigating an influenza pandemic are well known and have been tested in silico [4]. Traditional approaches, based on compartmentalized epidemiological models, can be found as well as other approaches like this individual example [5]. These approaches have provided promising results at the scale of an entire country but they are not sufficient to assess risk at the scale of interiors as this approach cannot embed the actual dynamic of local interaction [6]. Our approach studies the dynamics of the infection risk at the building level and offers an increased understanding of the impact of a localized intervention in both time and space.

This context is particularly well suited for agent-based modeling (ABM) [7]. With this approach, the profiles' of users as well as characteristics of the built environment can be considered. The characteristics can include the interactions among occupants as well as the interactions between the occupants and their environment within which they are operating. ABM enables rapid comparisons of different interventions and evaluation of their respective influence on the dynamics of the disease in order to determine an optimized combination of strategies such as the one developed by [8].

The model, developed using the GAMA Platform [9], explores successive simulations showing the effects of different interventions on the risk of infection inside of a specific space (e.g classrooms, building, campus) for a given population (student, teachers, etc). It allows rapid comparisons between interventions to assess their influence and efficacy on disease transmission to support the optimizations of combined strategies. Finally, this tool has been conceived as an interactive plat- form where decision makers can test and evaluate different policies that can be easily replicated on other spaces and potentially with other types of diseases.

The article is organized as follows. Section 2 presents in detail the implementation of the model. Section 3 compares different interventions and illustrates the use case of the different campuses of the University of Guadalajara. We finally conclude in section 4 on the perspective and limitations of such an approach.

2 Model

The model is described following the ODD [10] format to allow for better understanding and comparison with other models. It describes the person's behavior and the transmission characteristics of the virus.

2.1 Overview of the model

To evaluate and minimize the risk of infection for the users of the built environment, we created a model that estimates each person's potential exposure to the virus in each location considered. This was calculated day per day. The experiment consisted of people involved in daily activities in a given space, some of whom were assumed to be infected. We estimated the viral load to which non-infected individuals can be exposed throughout a day. We thus considered that exposure is a function of concentration and time. Three transmission vectors were assumed (droplets, fomites, and aerosols) and taken in account as shown in Figure 1. This approach gives the possibility not only to identify the risk of infection at the individual level but also at a macro level. The model then allows for the comparison of the mitigation efficiency of different interventions or policies.

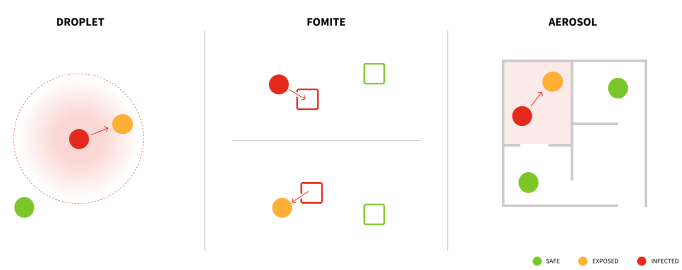

Fig. 1. Illustration of the three different modes of transmission of the virus. (a) droplets transmission: an infected person transmits a viral load to other humans at a given range. (b) Fomites transmission: an infected person transmits a viral load to a surface by contact. The surface then transmits a viral load to the people who touch it. (c) Aerosols transmission: light particles transmit an airborne viral load to people in the same room. Circles represent people and squares represent objects. Red: infectious, orange: exposed to the virus, green: safe..

2.2 Description of the model entities

People In our study, agents, representing individual ***people***, have individual behaviors that are determined according to personal characteristics such as agenda, age, occupation etc. Daily generic agendas are set up for people at UdeG and can be easily modified or extended. They describe activities such as working in an office, entering a room, going to a workstation, eating out, going home, etc, which are events occuring at specific moments. Agendas are created using an ad hoc generator: a set of scenario- dependant activities (with their target location and start time) for each agent. The choice of activities can be refined thanks to behavioral data extracted from questionnaires and interviews. Some activities lead to specific agent behaviors: for example, an agent working at the library may move to pick up a book or to talk with a colleague. In the same way, a queue system can optionally be used: if a queue policy is chosen, agents wishing to enter a room will have to queue to enter it (queue respecting a certain physical distance defined in parameter if possible). Agents have a fixed epidemiological status as *infected, susceptible*. Susceptible agents also have a *cumulated_viral_load* attribute which is a list of three elements representing the viral load received by droplets, fomites and aerosols transmission.

Space The spatial environment consists of a collection of spatial entities ***Room*** in which ***People*** can perform different kind of activities. Rooms are made of a list of entrances and places such as desks and/or chairs. Aerosol particles can spread the virus within a room. Each ***Room*** has a *viral_load* attribute that represents the virus concentration in the air and which is increased by the respiration of infected ***people*** and decreased by ventilation. Susceptible ***People*** receive a quantity of virus that is a function of that concentration (see 2.3). The viral concentration in each room is represented by a color gradient in order to easily identify risky areas.

2.3 Description of the model processes

Simulation Initialization A simulation is initialized by creating a synthetic population of agents **people**, and agents ***Room*** from floor plan files (.dxf or .gis). A compatible file should specify at least the four following layers as closed polylines: Walls; Entrance; Offices or Meeting rooms. Optional layer include Furniture, Chair, Sanitation and Toilets. The virtual pedestrian network is built by defining the walking zone, then applying a Delaunay triangulation to it to calculate the skeleton of the virtual pedestrian network. Other parameters are loaded from data files or can be directly modified to trigger different interventions. The number of generated people is set accordingly to the *density_scenario variable*. Based on a normal day activities, they are assigned schedules and targets such as work places that can be set by different methods:

- ***data***: if the floor plan contains a layer describing the desk layout then each people has a desk assigned to him as a target;

- ***distance***: people's targets are defined in order to respect a minimal distance between people (e.g $2m$);
- ***building occupancy***: the maximum number of people in a building is set by its capacity;
- ***room occupancy***: the maximum number of people in a room is set by its capacity.

Epidemic Status Initialization At the start of each simulation, a given amount of the people (*initial_nb_infected*) is set to the *infected* status, others are set to *susceptible*. Note that since the experiment duration is at the scale of the day, susceptible people do not have the time to turn infectious, thus the epidemiological status of agents remains unchanged during the whole simulation time. As a consequence, the risk of contamination is quantified by a person's viral load people.

Process Overview and Scheduling Simulations run during a given duration expressed in hour by (*time_spent*). Different agenda scenarios can be chosen, by default a person who enters the building by one of the entrances (chosen randomly) then goes to his assigned *working place* for a given amount of time (*time_spent*) and exits by the same entrance as he entered. A more typical day would be when people enter the building in the morning, go out for lunch and go back to work. The agenda or activity can easily be modified to add activity such as going to get a coffee or to the restrooms. Regarding people agents mobility, we use the method developed in [11]: agents walk on a continuous space and follow a pre-constructed virtual pedestrian network. They calculate the shortest path and follow the succession of nodes as intermediate objectives. The agents avoid collisions with others by using a repulsion mechanism inspired by the social force model [12]. More details on the pedestrian mobility can be found in [13, 11].

2.4 Virus propagation - Risk prediction

It is now established that respiratory viruses are transmitted in three different ways. Firstly, the virus can be transmitted by large respiratory droplets which is a vector of transmission to nearby persons. Secondly airborne transmission due to smaller droplets (aerosols) which stay suspended in the air and can travel longer distances can also lead to infection [14, 15]. Finally transmission can happen via a contaminated surface.

Droplets Most of the respiratory virus transmission occurs from large infected droplets that can be produced either by coughing, sneezing or even breathing in close proximity to another person. As a consequence, social distancing is considered as an efficient protection measure. Droplets are involved in a person-to-person infection, which means that an infected person transmits a viral load to other persons next to him/her. If a susceptible person is at a distance below a given threshold, he/she will receive a viral load per time step given by

$$v_d^0 \Delta t \big(1 - e_{separator}\big)\big(1 - e_{mask}^{emission}\big)\big(1 - e_{mask}^{reception}\big),$$

where Δt is the time step duration and v_d^0 the viral load transmitted per unit of time by an infected person. The quantity of virus transmitted is reduced by prevention measures like separators, a mask worn by the infected person and a mask worn by the susceptible person, with respective efficiency $e_{separator}$, $e_{mask}^{emission}$ and $e_{mask}^{reception}$.

Aerosols Studies have historically used a threshold of $5\mu m$ to differentiate between large and small particles, but researchers are now suggesting that a threshold of $100\mu m$ better differentiates aerodynamic behaviour of particles. Particles that would fall to the ground within $2m$ are likely to be $60-100\mu m$ in size. Investigators have also measured particle sizes of infectious aerosols and have shown that pathogens are most commonly found in small particle aerosols ($< 5\mu m$), which are airborne and breathable. Initially it was thought that airborne transmission of Covid-19 was unlikely, but growing evidence has highlighted that infectious microdroplets are small enough [14]. In the model, the concentration of virus in aerobic particles is considered for each room, and is increased due to the infected people's respiration and talking. At each time step, each infected person transmits a viral load that can be reduced by wearing masks. The viral load in the air is updated according to the formula

$$v_{air} := v_{air} + cV_{breath}(1 - e_{mask}^{emission})\Delta t$$

for each infected person, where V_{breath} is volume of air inspired/expired per unit of time, and c the viral concentration in the air expired.

The viral load in the air decays because of ventilation. After a time Δt, the viral load in the air is updated according to the formula

$$v_{air} := v_{air}(1 - d_{air})^{\Delta t}$$

where d_{air} is the decay rate per unit of time due to ventilation.

People get infected by breathing the air. The amount of viral load ingested by breathing decreases with masks. It is given by

$$(1 - e_{mask}^{reception})v_{air}\left(1 - \left(1 - \frac{V_{breath}}{V}\right)^{\Delta t}\right)$$

where V is the volume of the room. The same quantity of viral load is removed from the room's air.

Fomites latest research suggests that fomites are not a major route of transmission. However, even if attempts to culture the virus on surfaces were unsuccessful, Covid-19 can persist for days on inanimate surfaces. Surface agents has a viral load attribute which increases by interaction with infected individuals, decreases when transmitting the virus to a susceptible individual by contact, and decays at a given rate. Contamination of a surface per cycle and per infected person is given by

$$v_{surface} := v_{surface} + v_f^0 \Delta t \big(1 - e_{mask}^{emission}\big)$$

where v_f^0 is the viral load transmitted by an infected person per unit of time. Decay per time step is given by

$$v_{surface} := v_{surface}(1-d)^{\Delta t}$$

where d is the decay rate per unit of time. When in contact with a susceptible person during a time Δt, the viral load on the surface decreases and is updated according to the following formula:

$$v_{surface} := v_{surface}(1-r)^{\Delta t}$$

where $r \in [0,1]$ is the proportion of virus transmitted to the person per unit of time. The actual viral load that is ingested through hand-to-mouth after touching an infected surface is decreased by wearing a mask. The amount of viral load ingested is then

$$v_{surface} T_{HtM} \left(1 - e_{mask}^{reception}\right) \left(1 - (1-r)^{\Delta t}\right)$$

where T_{HtM} is the proportion of virus transmitted from the hand to the mouth.

2.5 Parameters

Some parameters are set based on values found in the literature, while others are estimated. Values are shown in table 1. We normalize the viral load transmitted via droplets to 1, and estimate the other viral loads relatively. It is suggested in [16] that the mask efficiency is high (above 70%). Masks prove to be a good protection while worn by emitters, receivers, but also reduce transmission via fomites. The proportion of the droplets which evaporate to aerosols is not well known. The proportion of small aerosols is larger, but the viral load per particle is smaller [17]. The proportion of contamination through aerosol is unclear. As a consequence, we choose to set parameter c in order to emit an equivalent viral load to the droplets. Fomite parameters are estimated bearing in mind that the transmission is supposed to be very low [16]. The decay rate on surface is estimated based on experiments on plastic in [18]. Ventilation parameter is set in order to renew 98% of the air of a room in 10 hours (natural ventilation) or 1 hour (forced ventilation).

2.6 Outputs

We illustrate the possibilities of the proposed model on a specific case study (one floor of the MIT Media Lab) in order to compare the impact of separated

variable	definition	value	source
v_d^0	viral load transmitted per unit of time (droplets)	1 s^{-1}	set as a reference
v_f^0	viral load transmitted per unit of time on surfaces	0.25 s^{-1}	estimated
V_{breath}	air volume inspired or expired	8 $L.mn^{-1}$	[16]
c	viral concentration in breath	10 $L^{-1}.mn^{-1}$	[16, 17]
T_{HtM}	transfer rate from hand to mouth	30%	estimated
r	virus transfer rate from surface to hand when	0.01 s^{-1}	estimated
d_{air}	virus load decay rate: by natural ventilation	10^{-4}	estimated
	by forced ventilation	10^{-3}	estimated
d	virus load decay rate on surface	3.10^{-5}	[18]
$e_{mask}^{emission}$	mask efficiency: percentage of the viral load emission being blocked	70%	[16]
$e_{mask}^{reception}$	mask efficiency: percentage of the viral load reception being blocked	70%	[16]
$e_{separator}$	separator efficiency: percentage of particles blocked	90%	estimated

Table 1. Parameters used in the model. Variable with no reference have been estimated.

interventions against a reference scenario without any interventions (Figure 2). The outputs provide global indicators about the population and a more detailed visualisation of the status of each individual, for the Media Lab building. This allows comparison of different kinds of interventions. Global indicators consist of time series representing the temporal evolution of the viral load to which people have been exposed to for each type of contamination, and a histogram representing the distribution of the population into three levels of risk (low, medium and high) to which each individual has been exposed. Simulations also provide an animated spatial visualisation of the building (floor plan) with the location and epidemiological status of people (infected, or low/medium/high risk).

3 Results

3.1 Stochasticity Sensitivity Analysis

We first analyze the impact of the randomness of the simulations on the three types of transmissions (droplet, contaminated surface and aerosol). The main objective is to find a threshold number of replicates beyond which the mean values of such indicators are sufficiently accurate. To do this, we compare the output of these three indicators between replicates of the simulation. We undertake this exploration on a typical example of use of the model (one floor of the MIT Media Lab) with no specific intervention. We perform 100 replicates of such a simulation and compare the variability of the results with different number of replicates. We observe that with a low number of replicates the standard error is very high. With 20 replicates, the standard error is low for the droplet

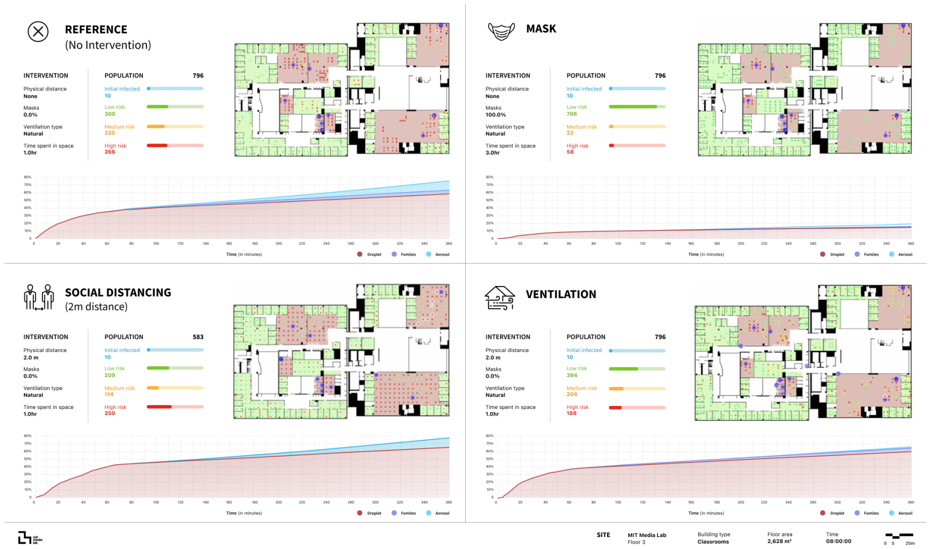

Fig. 2. Comparison of the three interventions with the reference scenario, for the MIT Media Lab building. 1) no intervention, 2) use of masks, 3) social distancing and lowering the density, and 4) replacing the natural ventilation by air conditioning.

transmission but remains high for the two other transmission types. With 50 replicates, the difference is very slight for all indicators. Increasing the number of replicates further beyond 50 does not have a great impact on the aggregate trend of the simulation results. For the study of the scenario presented in the following section, we decide to set the number of replicates at 50 in order to minimize the required computation time while maintaining a good statistical accuracy.

3.2 Use cases: University of Guadalajara (UdeG) and MIT Media Lab

The public University of Guadalajara (UdeG) leads a complex educational ecosystem that includes more than 300.000 students, 16.000 staff members, which are distributed on several campuses over Guadalajara City and the state of Jalisco, Mexico. In Mexico, the UdeG sets up a general protocol to reopen its facilities based on international organizations' recommendations. We select for this work three of UdG campuses (CUCS classroom, CUAAD office, CUCEA library, see Figure 3), in addition to the MIT Media Lab.

In the following subsections, we analyse the exposure to the virus through the three ways of transmission, then we compare the effectiveness of the combinations of different interventions including wearing masks (intervention 1), social distancing (intervention 2) and ventilation (intervention 3). For each scenario and each site, we run a batch of 50 replications and report the mean values of

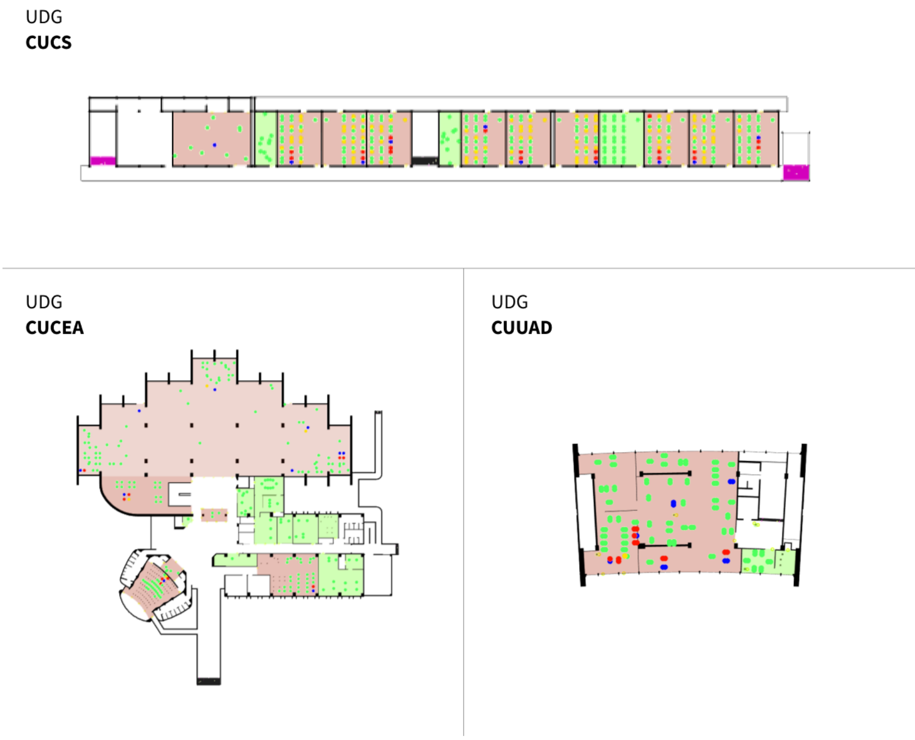

Fig. 3. The model has been experimented on three sites in the UdG university. The 3 sites have been chosen in order to cover different use cases. CUCS represents the first floor of a building made of 10 different classrooms and two meeting rooms. CUCEA is a mix between classrooms, meeting rooms and contains also a library used as a common area. CUAAD is made of meeting rooms and classrooms.

the indicators.Such scenarios are built so that each visualization highlights the concepts explained in section 2 in a way that students and staff can quickly understand.

3.3 Analysis of the virus transmission without intervention

The relative importance of the three ways to be contaminated are shown in Figure 4. The visual outputs and time series are presented only for the Media Lab on Figure 2.

For all use cases, transmission by droplets appears to be the most effective way, while fomites is the least effective. Without any intervention, people are at high risk when in the same room as an infected person, even if the room size is large, highlighting a high transmission rate despite a relatively modest contribution in the viral load. Scarce presence of people at high risk in rooms without infected people suggests that they were exposed at close range to infected

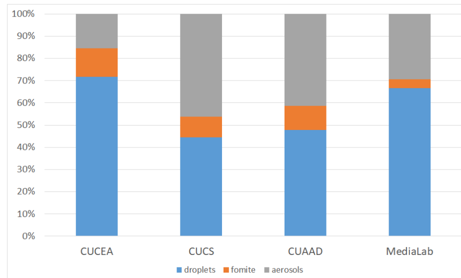

Fig. 4. Comparison of the exposure to the virus through the different vectors of transmission for the different UdG sites.

people when moving. It is confirmed by the fact that the viral load time series show a fast increase of droplet contamination at the beginning of the simulation and at the end, when people go to their desk or go away. Aerosols contamination starts later, since the quantity of virus in the air slowly increases with time.

As shown on Figure 4, the configuration and usage of the buildings impacts the relative proportions of exposure to droplets, fomites and aerosols: large rooms like the library in CUCEA are less favourable to the transmission via aerosols.

3.4 Comparison of different combinations of interventions

We study the impact of three interventions: 1) use of masks, 2) social distancing and lowering the density and 3) replacing the natural ventilation using air conditioning. Simulations outputs are presented in Figure 2. The risk reduction is compared for the different combinations of interventions. The mean risk reductions for each combination are shown in Table 2.

Site	Interventions						
	1	2	3	1+2	1+3	2+3	1+2+3
CUCS	90.4%	47.7%	31.6%	95.2%	93.4%	78.2%	98.0%
CUAAD	90.4%	56.3%	27.3%	96.0%	93.1%	83.4%	98.5%
CUCEA	91.1%	65.5%	17.9%	97.0%	92.2%	76.3%	97.9%
Media Lab	90.3%	15,0%	14,0%	92,1%	92.2%	33.2%	94.3%

Table 2. Risk reduction measured as the percentage of drop in cumulative viral load relative to a scenario without any intervention, for different use cases and for all kinds of combinations of interventions (1: masks, 2: social distance and lower density, 3: ventilation).

It appears that the most efficient single intervention is the use of masks. Indeed, under the assumption that high filtering capability is provided and that they are used properly, they provide a protection against the three ways of contamination. Masks effectiveness is homogeneous among the different scenarios.

In Figure 2.1, wearing masks significantly decreases the exposure to the virus in droplets and aerosols, the vast majority of people being at low risk. However people at a close distance of infected individuals seem to be still at high risk, highlighting that proximity still plays an important role in disease transmission.

Social distancing comes in second, apart for the Media Lab. It provides good protection against droplets when people are at their desks, but less when they pass each other while moving. This intervention comes along with a lower density. In Figure 2.2, it appears that the building occupancy drops from 796 to 583 since the desks layout has to be changed in order to fulfill a minimum distance constraint. The effectiveness of such a measure highly depends on the original space use and configuration: desk optimization has a lower effect in Media Lab since the original layout already has large space between desks.

Finally, ventilation decreases the concentration of aerosols and thus exposure to the airborne virus, but not to fomites and droplets. As a consequence, it is the least effective intervention. It might prove to be more efficient for longer durations, since the exposition to aerosols increases with time. Ventilation is more efficient within buildings with small rooms (CUCS, CUAAD), and should be recommended accordingly. A combination of two interventions increases the protection, 1+2 and 1+3 being more efficient than 2+3. Combination 1+2+3 marginally increases the protection compared to 1+2 alone (less than 2.8%).

Complying with the CDC recommendation to wearing masks, social distance and ventilation comes at a cost that may be difficult to handle. If wearing mask is cheap and easy to impose, ventilation may require works on buildings. Social distance maybe the harder to comply, since a lower building occupancy may require that students partly attend classes from home. The logistic for such an intervention may also be a barrier. This study suggests that the most effective intervention is wearing masks. It can be complemented with others interventions, but since they marginally increase the effectiveness, they should be considered as secondary, and may be omitted in case their cost or logistic is too important.

4 Conclusion and perspective

This model has been used to inform the academic community of UdeG about efficient ways to protect their community from the spread of Covid-19. Graphical and quantitative outputs have proven to be a good medium to illustrate the way the pandemic propagates and the efficiency of the different recommendations. Once the different simulation scenarios were analyzed and the most appropriate forecasts were developed for the use of the different spaces on campuses, the results were disseminated in an educational video and campaign, in order to educate people about the benefits of complying with the CDC recommendations. Further developments of the model will aim at providing not only a better prediction of the risk of contamination but also a more realistic agent behavior in order to take in account other dynamics. It is however, important to consider the results from this work with care, since there is still a major uncertainty on the relative importance of aerosols and droplets in the chain of contamination.

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