City-scale model for COVID-19 epidemiology with mobility and social activities represented by a set of hidden Markov models

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Abstract

Background and Objective: SARS-CoV-2 emerged by the end of 2019 and became a global pandemic due to its rapid spread. Various outbreaks of the disease in different parts of the world have been studied, and epidemiological analyses of these outbreaks have been useful for developing models with the aim of tracking and predicting the spread of epidemics. In this paper, an agent-based model that predicts the local daily evolution of the number of people hospitalized in intensive care due to COVID-19 is presented.

Methods: An agent-based model has been developed, taking into consideration the most relevant characteristics of the geography and climate of a mid-size city, its population and pathology statistics, and its social customs and mobility, including the state of public transportation. In addition to these inputs, the different phases of isolation and social distancing are also taken into account. By means of a set of hidden Markov models, the system captures and reproduces virus transmission associated with the stochastic nature of people's mobility and activities in the city. The spread of the virus in the host is also simulated by following the stages of the disease and by considering the existence of comorbidities and the proportion of asymptomatic carriers.

Results: As a case study, the model was applied to Paraná city (Entre Ríos, Argentina) in the second half of 2020. The model adequately predicts the daily evolution of people hospitalized in intensive care due to COVID-19. This adequacy is reflected by the fact that the prediction of the model (including its dispersion), as with the data reported in the field, never exceeded 90% of the capacity of beds installed in the city. In addition, other epidemiological variables of interest, with discrimination by age range, were also adequately reproduced, such as the number of deaths, reported cases, and asymptomatic individuals.

Conclusions: The model can be used to predict the most likely evolution of the number of cases and hospital bed occupancy in the short term. By adjusting the model to match the data on

hospitalizations in intensive care units and deaths due to COVID-19, it is possible to analyze the impact of isolation and social distancing measures on the disease spread dynamics. In addition, it allows for simulating combinations of characteristics that would lead to a potential collapse in the health system due to lack of infrastructure as well as predicting the impact of social events or increases in people's mobility.

Keywords: Agent-based model; hidden Markov model; COVID-19; epidemiology; georeferencing; virus transmission; virus spread

1. INTRODUCTION

In March 2020, the World Health Organization characterized COVID-19 as a pandemic, and various countries declared a state of emergency. By this time, the novel coronavirus SARS-CoV-2 that produced the COVID-19 outbreak had infected more than 270,000 people all over the world and killed more than 11,300 [1].

According to current epidemiological reports, this pandemic has characteristics that are rarely seen in other infectious diseases [2]. Some of the particularities of COVID-19 are its high basic reproduction number [3]; a possible asymptomatic infectious period of up to 14 days, in which there is a group of individuals with no symptoms and the disease can be detected only through a serological test; and great variability in disease evolution and clinical outcomes [4]. It has been proven that the dynamics of this epidemic vary primarily according to the climate [5], local social and health habits [6]-[10], comorbidities [8] and age range [9], among other variables. The epidemiological analysis of the different outbreaks of this disease, which have been recorded worldwide, has helped develop different models, primarily mathematical, to track and anticipate the spread of epidemics [11]–[14].

The multiplicity of factors influencing this pandemic and the limited results of some classical models [11] [14]-[16] have generated a problem that is yet to be solved. A different approach is needed, and it is necessary to focus on the formulation of more realistic models that jointly include specific social, environmental and geographic characteristics for each area under study.

Much of the reported literature on the modeling and simulation of epidemics, in particular COVID-19, proposes global models based on differential equations on the susceptible, exposed, infected, and recovered (SEIR), with their different variants being adapted to this disease [15], [16].

The application of models based on machine learning (ML) and artificial intelligence (AI) to obtain predictions [17] and determine the characteristics of the epidemiological dynamics of COVID-19 [18]-[21] has also been explored. These types of models, which are classified as fully data-driven models, have the limitation of primarily fitting the data with which they were trained, lacking the ability to generalize well to changes in any parameter of the environment or the range of input values [22]. Another limitation of this approach is the lack of explainability of the obtained results [23].

Local or fine-grained models [24] have also been used, including agent-based models (ABMs) [6], [9], [25], [26]. These models allow for greater expressiveness and control of different aspects of the epidemic, the inclusion of the randomness inherent in these systems, and the possibility of time-space monitoring of the simulation runs [6], [7], [27]. Another advantage is their ease of testing different scenarios and their relative impact on the results ("What if?"). However, they require greater computational power and access to a large amount of local data to be adapted to specific situations. Table 2 presents a comparative summary of the main characteristics of each type of model.

ABMs are computational modeling and simulation methods used to study the organization and dynamics of complex systems. They consist of an artificial society integrated by autonomous and heterogeneous agents that interact in a non-trivial way with each other and with the environment, according to specific rules, forming a social architecture [28]-[31]. The social aspect is given by the heterogeneity, autonomy, interdependence, and social embedding that characterize the computational agents [10], [32]. To our knowledge, few models with these characteristics have been applied to COVID-19 [6], [7], [10], [33]–[35]. Furthermore, most of them have been designed for specific situations in some cities, regions or countries, and it is difficult to extrapolate them to new situations, because a great deal of scientific and technical knowledge is required for this purpose.

This paper proposes a novel ABM model that can incorporate local factors, such as social, cultural, geographical, and climatological variables, that are linked to the epidemic under study and to its transmission modes. The aim is to provide an alternative tool that allows researchers to predict the impact of different social and health policies on disease evolution. The model is called the *Agent-based model for COVID-19 Simulation* (AbCSim) and allows for the modeling of a group of people with COVID-19, either symptomatic or asymptomatic, together with those considered to be susceptible or recovered populations [36] during the first year of the reported pandemic. This model considers the complexity of the dynamics underlying the pathology and interpersonal relationships of the population, along with geographical and climatological information relevant to the pandemic. In addition, it implements a host transmission block based on a set of hidden Markov models (HMM) [37], [38], which reflect the main aspects of the mobility and social activities of the agents within the modeled geographical region. AbCSim runs on the computational simulation platform Repast [39] and is open source (accessible via GitHub). The proposed model allows for the simulation of an entire population, on an individual basis, at the city scale (or larger). This study presents the complete structure of the model, together with the mathematical and methodological details of its implementation, allowing for appropriate reproducibility. To validate the model, Parana city (Entre Ríos, Argentina)[1] was used as a case study and tested under different situations to predict the local evolution of the disease during 2020. In a previous short paper, the usefulness of the model's predictions was shown for a specific case study in the city of La Rioja (La Rioja, Argentina) [40], but the complete structure, mathematical and methodological details have not yet been published. This is the main objective of the present work, in which the model was validated with data from Paraná city (Entre Ríos, Argentina) under different situations to predict the local evolution of the disease during 2020.

Table 1: Nomenclature and notation used in the text.

Nomenclature	
ABM	Agent-based model
AbCSim	Agent-based COVID-19 Simulator
Ha	Human agent
GIS	Geographic information system
HMM	Hidden Markov Model
ICU	Intensive Care Unit
l	Place
e	Age range
h	Time slot
η	Probability of changing to asymptomatic
γ	Probability of going to ICU
ω	Probability of death in ICU
β	Probability of transmission
$1/\alpha$	Incubation period (days)
$1/\mu$	Infection period (days)
$1/\Psi$	ICU stay (days)

Table 2: Characteristics of the different technique-based models used here and the corresponding references.

Model type	**Level/ Scale**	**Guided/ driven**	**Complexity**	**Explain-ability**	**What if?**	**Reference**
Mathematical/ SEIR	Macro	Knowledge	Low	High	Limited	[1], [3], [4], [6], [7], [11]-[16]
AI/ML	Any	Data	Medium/ High (Deep)	Low	No	[17]-[21], [23]
ABM	Micro/local	Knowledge/ Data	High	High	Yes	[6], [9], [10], [25]-[36], [40]

[1] https://www.parana.gob.ar/institucional

2. METHODS.

2.1. Description and general scheme of the model

Figure 1 presents the general scheme of the model with different levels of detail [41]. The first general level broadly represents the complete model (black block), with its initial conditions, inputs, and outputs. The second level shows the main blocks of the system (blue blocks): a block for simulating *the spread of the virus for each host* (left side) and another for the *transmission of the disease between hosts* (right side), as proposed by other authors. The next level (green blocks) shows the sub-models of *epidemiological characterization* and the *infectivity* for each agent and their corresponding parameters. It also presents *interpersonal contact, location* and *mobility/activity* sub-models and the specific parameters for this sub-model. Lastly, the third level also shows the *transport* and *infectious trail* sub-models (magenta blocks). Each sub-model will be described in detail in the following sections.

The model structure is presented in the UML (Unified Modeling Language) diagram shown in **Appendix A,** an ODD protocol[2] based detailed description of the model is presented in **Appendix B**, and its complete code is accessible via GitHub[3].

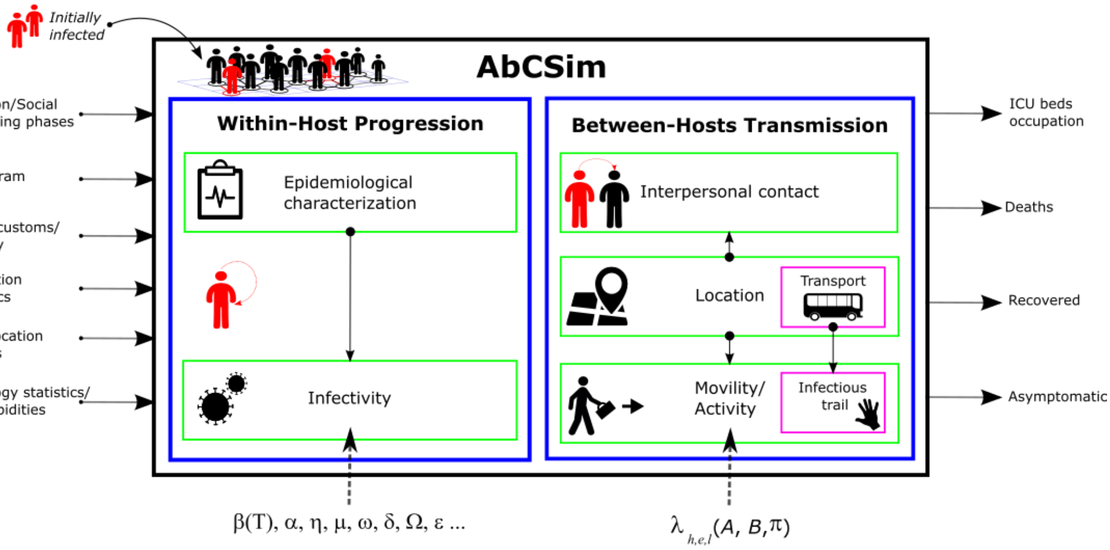

Figure 1: AbCSim block diagram: General model (black block) with inputs, outputs (horizontal solid line arrows) and initial conditions (curved arrows); main functional blocks (blue left and right-side blocks) and the corresponding sub-models for each block (green and magenta blocks). Vertical solid line arrows represent the relationships between various model elements, and vertical dotted line arrows represent the corresponding parameters (see details in text).

2.2. Agents, attributes, and general behaviors.

Since it is an ABM, the core of the model is constituted by agents named *humans* (Has). Each Ha can acquire and transmit the SARS-CoV-2 virus, change the symptoms and health state

[2] V. Grimm, U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, and S. F. Railsback, "The ODD protocol: A review and first update," Ecol. Modell., vol. 221, no. 23, pp. 2760–2768, 2010.

[3] https://github.com/Repastero/GeoCOVID-19

according to the infection spread *within the host*, and change behaviors accordingly (*infectivity* sub-model, Section 2.3.1). In addition, each Ha has specific characteristics and attributes corresponding to risk factors and comorbidities (*epidemiological characterization* sub-model, Section 2.3.2).

The most important relationships *between hosts that propitiate virus transmission* regarding COVID-19 epidemiology are represented in the *interpersonal contact* sub-model (Section 2.4.1). This sub-model also presents Ha relationships with each other, with the plots of land, and with the environment. These relationships are affected by the average distance in the different places they attend, how long they stay, and the observance of mask use and social distancing rules (Sections 2.4.1 and 2.4.2).

The location of each Ha is simulated by the *location* sub-model, in which a specific geographic information system (GIS) module of the Repast platform is used, which will be further described in Section 2.4.2. This system makes it possible to differentiate and characterize family residences, buildings, stores, squares, means of transportation and other relevant locations where people stay. The geographical environment and each plot in which the city is subdivided are defined as agents, with their own methods and attributes. Furthermore, the most important means of public transportation are represented in the model as a specific location where people gather. This characteristic can be observed in the *transportation* sub-model (Section 2.4.2.1). The level of detail and the quality of the specific geographical information in this system are vital to represent the mobility and activities of each Ha in this simulated society accurately.

Each Ha has a specific behavior according to their age range, habits, and the neighborhood where s/he lives, which are randomly assigned at the beginning of each simulation in accordance with the population statistics for the city. Considering this setup, each Ha moves individually according to probabilities ($A \epsilon \lambda_{h,e,l}(A, B, \pi)$) associated with the state change matrices of a set $\lambda_{h,e,l}$ of HMM that represent the *mobility/activity* sub-model. Each HMM corresponds to a place (l) (neighborhood/city/area) where Ha lives, to their age range (e), and to the time slot (h) at the time of the simulation. The description of this sub-model will be presented in Section 2.4.3. Lastly, the permanence of an active virus in different locations/environments is represented by the *infectious trail* sub-model that is described in Section 2.4.3.1.

2.3. Block of Within-Host Progression.

2.3.1. Infectivity Sub-model.

The infectivity sub-model is based on a mathematical model proposed by Arenas et al. [42], which was translated to Repast as the viral spread process in Ha. Each Ha has a state attribute according to one of these seven epidemiological compartments in which the population is divided: **S**: susceptible; **E**: latent or exposed; **I**: symptomatic infectious; **A**: asymptomatic infectious; **R**: recovered; **D**: dead or **H**: hospitalized. Figure 2 shows the different components, relationships, and parameters of this sub-model.

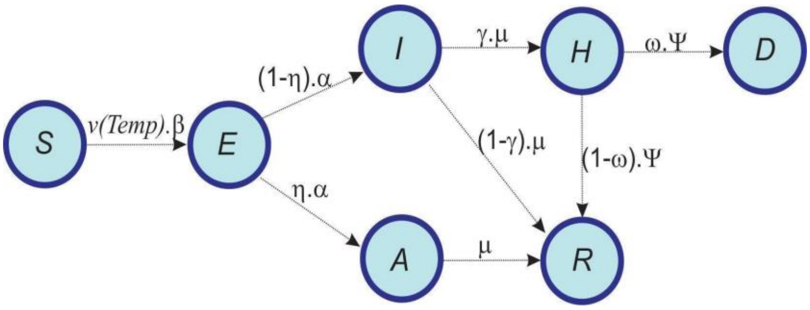

Figure 2: Infectivity sub-model with seven compartments: **S**: susceptible; **E**: latent or exposed; **I**: symptomatic infectious; **A**: asymptomatic infectious; **R**: recovered; **D**: dead, and **H**: hospitalized. Modified from Arenas et al. [42] (see parameter details in the text).

This sub-model comprises the main pandemic-specific COVID-19 disease progression in a characteristic host, excluding the level of molecular biological mechanisms [43], [44], because they are beyond the scope of this work. One such important epidemiological effect is caused by asymptomatic infectious individuals (**A**) or individuals with mild symptoms. The fraction of individuals requiring hospitalization in intensive care (**H**) is also considered, and it is assumed that all Ha have the possibility of accessing a respiratory ventilator. This is a model simplification that will be completed in future works. In any case, during the study period, the number of intensive care unit (ICU) patients did not exceed the number of ventilators available in the city.

Considering the aforementioned characteristics of human agents, this sub-model operates as follows: the susceptible Ha becomes infected with a probability β due to interpersonal contact with another infected Ha who is either symptomatic (**I**) or asymptomatic (**A**). This probability of infection is modulated by variable *v*, which is dependent on the daily mean temperature. If the susceptible individual (**S**) becomes infected, Ha becomes part of the population exposed to the virus (**E**). Exposed individuals, at 1/α days later, become asymptomatic or symptomatic, according to a characteristic probability η, depending on the Ha's age range. Once infected, there are two possibilities. The first option is that Ha requires hospitalization (**H**) in the ICU, with a specific probability γ, according to the Ha's age range, comorbidities, and risk factors. Comorbidities and risk factors are attributes of each Ha that increase the probability of moving to the ICU. If Ha is not transferred to the ICU after 1/(μ) days, then they are considered recovered and not reinfected, at least for an average period of 11 months, according to [45]. During their stay in the ICU, these individuals have a death probability of ω [46] after an average period of 1/Ψ days [47], [48]. After this period, the Ha vacates the ICU bed and moves to the recovered (**R**) compartment.

The Ha population was divided into five age ranges: children, young people, adults, older adults and elderly people. Transition constants between epidemiological compartments presented in Figure 2 are specific to each age range and are shown in Table 3.

Table 3: Values of the infectivity sub-model parameters used here. Those for which the mean value ± standard deviation is specified have a normal probability distribution. Adapted from [42].

Age range Parameter	Children	Young people	Adults	Older adults	Elderly people
η	0.74	0.58	0.42	0.26	0.10
γ	0.00011	0.00031	0.00081	0.0464	0.3051
ω	0.42	0.42	0.42	0.42	0.42
β	0.26	0.26	0.26	0.26	0.26
$\frac{1}{\alpha}$ (days)	5.2 ± 1	5.2 ± 1	5.2 ± 1	5.2 ± 1	5.2 ± 1
$\frac{1}{\mu}$(days)	5 ± 1	5 ± 1	5 ± 1	5 ± 1	5 ± 1
$\frac{1}{\psi}$(days)	4 ± 1	4 ± 1	4 ± 1	4 ± 1	4 ± 1

The infectivity sub-model changes the behavior of the Ha according to their epidemiological compartment. If Ha is in the Susceptible compartment, then Ha meets the daily activities and movements pre-established as attributes and defined by the *Mobility* sub-model. However, if Ha is in a different compartment from Susceptible or Exposed, then they stop moving, since it is assumed that they remains at home to avoid transmitting the disease to other Has. From that moment on, the household members are in the exposed compartment.

Lastly, in AbCSim, the transmission probability from interpersonal contact is a parameter linked not only to strictly epidemiological aspects, because β is also multiplied or modulated by the variable *v*, which evolves throughout the year and is inversely proportional to the daily mean temperature. According to studies that define COVID-19 as a seasonal disease [49]–[52], the β value is affected by the variable *v*(*Temp*), which reaches its maximum value (the unit) on July 15 and its lowest value (0.5) on January 15, when the daily mean temperature is higher in the southern hemisphere.

In other words, the progression of the illness in the host can be defined as a stochastic Markov chain model in which the patient is assumed to always be in one of a finite number of health states (called Markov states). These states are exhaustive (i.e., all possible) and mutually exclusive (an individual cannot be in two states at the same time) [42]. Therefore, the popular epidemiological compartmental models first formulated by Kermak & Mac Kendrik [53] can be viewed as Markov chain models (in which looped arrows are intentionally omitted for simplicity).

2.3.2. Epidemiological Characterization Sub-model

As mentioned in the previous section, each Ha has specific epidemiological values that affect the *infectivity* sub-model parameters shown in Table 3. Among these attributes, we highlight the existence of comorbidities and risk factors and the existence of symptomatic infected household members. Comorbidities increase the probability γ of going from infected to inpatient in the ICU according to a percentage value.

Lastly, there are two attributes linked to Ha behavior that have epidemiological consequences: the observance of social distancing (*distancing*) and the effectiveness and observance of mask use (*mask*). Although both attributes complete the epidemiological characterization of each agent, its functioning is described in the *interpersonal contact* sub-model (Section 2.4.1).

2.4. Host Spread Block

2.4.1. Interpersonal Contact Sub-model

For each Ha, there is a method that measures whether there is another agent within a 2 meter range (contagion distance) [54]–[56]. If this proximity lasts for 15 minutes or longer and either agent is infected (symptomatic or asymptomatic), then the epidemiological state attribute of the non-infected Ha changes to exposed (**E**), with probability $v(Temp)*\beta$.

For each Ha, the model considers the current national definition of "close contact"[4]. This routine causes an automatic state change from susceptible (**S**) to exposed (**E**) for the household members who live with a symptomatic infected Ha, regardless of whether interpersonal contact has been corroborated. In addition, as previously mentioned, each Ha has an attribute that expresses the observance of mask use. This attribute means that β is affected by another coefficient, named *mask*. This coefficient modulates β when there is close contact, subtracting 30% [25], [33], [57]-[59] of its value when Ha shows a high level of observant mask use. When this level of observance is low, then the mask coefficient is not applied.

Lastly, this sub-model considers an attribute of each Ha that is defined by the level of observance of social distancing, named *distancing*. This attribute has two possible values: high or low. If Ha has a high level of observance, they check that there is no other agent within a diameter of 1.8 m before taking any position in the geographical grid that does not correspond to their home. If this condition is verified, then the Ha takes this place. If not, they wait until the corresponding capacity allows. However, if distancing has a low value, then when this Ha moves, it takes the corresponding place, regardless of the distance between different Has.

2.4.2. Location Sub-model

The GIS tools included in Repast were used to achieve an approximate representation of locations where citizens live, work, consume and perform leisure activities (see **Appendix C**).

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[4] https://www.argentina.gob.ar/salud/coronavirus-COVID-19/Identificacion-y-seguimiento-de-contactos

This information, together with movements verified during the day, configures the gregarious habits of each Ha. These habits were determined through 441 individual field surveys, which complied with age and sex quotas and with the requirements of the Ethics Committee in charge of evaluating and authorizing the structure, anonymization, and informed consent of the surveys[5].

As described in **Appendix C**, city grid maps were used to represent buildings as houses, workplaces, shops, recreational places, etc., provided by the Land Registry Office of the Paraná Municipality. Tools such as Google Maps and Google Places® were also used[6], with which a first mapping of different areas of the city under study was obtained. A visual inspection of the plots and their labels was then performed in situ to verify the information provided by the aforementioned resources. In this way, the GIS map was completed with the field survey assisted by tracking tools based on GPS. With this information in the system start routine, each Ha is assigned the attributes linked to this sub-model until the entire map is filled with the number of Has corresponding to each plot of land. Figure 3 shows a map of Paraná city neighborhoods or districts No. 2 and No. 11 with a level of detail showing the main AbCSim places of interest and activities performed at those places.

Figure 3: GIS map of areas No. 2 (left) and No. 11 (right) in Paraná city used for the location sub-model.

2.4.2.1. Transportation Sub-model

This block represents the influence that public transportation has on COVID-19 epidemiology. Different public transportation lines were represented as places or fixed positions on the map, where each bus stop is a plot of 10x4 m. This simplification aims to represent only the main characteristics of public transportation dynamics relevant to this study. A Ha can enter

[5] Comité Asesor de Ética y Seguridad en el Trabajo Experimental (CEYSTE), CCT Santa Fe, CONICET, Argentina, https://santafe.conicet.gov.ar/ceyste/, Expte. CEYSTE- CES-00622/2021

[6] Google. (n.d.) [Map of Entre Rios, Argentina at Google maps.] Accessed in 2020, from: https://www.google.com.ar/maps/@-31.7446799,-60.512176, 13 z

this plot once every 20 min (average frequency of local public transportation) and remain at an average distance of 2 m for 20 min. The distancing guideline is not met only for one minute, which would represent the time that it takes to go from the entrance door to the seat and from the seat to the exit door. After 20 minutes, each Ha can either move to a new position on the map or stay in the transportation position for another equal period (depending on a transition probability defined by the mobility/activity sub-model, which will be discussed in the next section).

As described above, public transportation also has a specific capacity, but there is a probability of close contact, which is modulated by the Ha's observance of mask use and social distancing (as it occurs in any other location of the model).

2.4.3. Mobility/Activity Sub-model

This sub-model simulates the mobility or movements of human agents living in a district or neighborhood of the model, considering the simulated age range and time slot. It also establishes the type of activity that each Ha will perform in the location where they will be during the next period of time under consideration. Some of these activities are unique to each Ha throughout the simulation (e.g., type and location of work or study), and others are obtained at the moment they are to be conducted (e.g., type of leisure activity).

The study and modeling of human mobility is an important and active field of current research [60]. In epidemiology, understanding mobility patterns is fundamental since they are directly related to the dynamics of epidemic expansion, both temporally and spatially. There are multiple models of human mobility, which are inspired by physical formulas and statistical or heuristic definitions, among others. One of the simplest but least realistic is the random walk model. There are also models that take advantage of a given regularity in human activities to propose a daily schedule or agenda for each individual [10], [27], [52], [59]. In this paper, we propose the use of Markov models for the modeling of agent mobility since they have demonstrated a good relationship between complexity and realism, with good results in other applications. Moreover, they have a well-studied theory with specific methods for parameter estimation.

AbCSim generates a series of waypoints in specific geographical locations from a set of HMMs to calculate the position of each Ha at each instant [63]. Each of these HMMs defines the probabilities of moving from one position to another, depending on the position occupied by the Ha in the previous instant and on the activities defined for the Ha's particular attributes. It is considered that the behavior linked to each Ha’s mobility is different at different times of the day, so specific HMMs are generated for different time slots, and the same variation occurs for age ranges. According to their age range, each Ha has a characteristic type of mobility and activities shared by all the human agents in the same neighborhood or district.

Ventilation in streets can be considered complete, and thus, the contagion probability in these places is assumed to be practically negligible [62], [63]. Therefore, assuming that virus transmission in streets has no impact on the model, it is postulated that mobility on foot from one plot to another is immediate for the Ha. As described in the previous section, only the dynamics of mobility by public transportation are represented, where appropriate, since this type of mobility is considered a possible activity for the Others state, which will be discussed below.

The set of HMMs that comprises the mobility sub-model is defined as $\lambda_{h,e,l}(A, B, \pi)$. There is a specific $\lambda_{h,e,l}$ HMM for each Ha based on the age range (e), neighborhood (l) and time slot (h) corresponding to the simulation time.

All HMMs have four states, as shown in the state graph in Figure 4. Each state represents a different type of location or activity, namely, home (**C**), work (**T**), leisure (**E**) and others (**O**). In turn, each HMM has its own transition matrix $A_{h,e,l}$, which presents state change probabilities $a_{h,e,l}(i,j)$ to move from one type of location (j) to another (i); a matrix $B_{h,e,l}$ that shows output probabilities $b_{h,e,l}(k,i)$ for each state (for the k possible places where Ha in state i could go to) and a vector π of initial location probabilities. Vector π is always (1,0,0,0) for the beginning of the day, as it is assumed that all Has start the day at home.

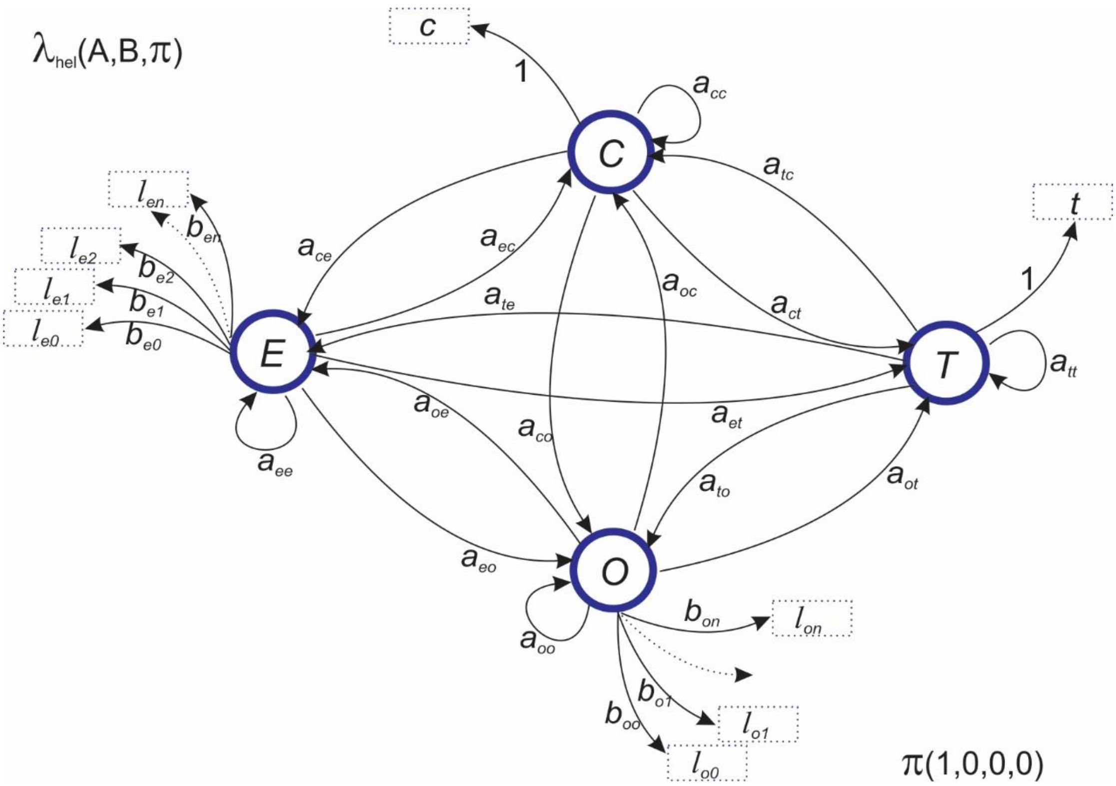

Figure 4: State graph of a Markov sub-model. The four states, circled, represent **C**: house; **T**: work; **E**: leisure; and **O**: others. Rectangular blocks show possible outputs for each state, i.e., each waypoint. States **H** and **W** have only one possible output (defined in the attributes of each Ha); therefore, that output has a probability 1 of being chosen. State **L** has different possible outputs selected from a list with locations l_{en} that depend on the Ha's neighborhood. State **O** selects its output randomly.

The possible states have the following specific characteristics:

- **C**: This location represents the Ha's home and, therefore, has only one possible outcome. The specific location on the geographical map of the city that means the output for this state is defined as an attribute for each Ha and is part of the *location* sub-model. This attribute is randomly chosen from a geographical area of the city defined as habitable at the beginning of the run and is the same throughout the simulation.
- **T**: This state represents the work or study location of each Ha. This point on the geographical map can be shared by multiple human agents. For some Has, it coincides with that of their home (for those who do not work or study). The work/study location is fixed for each Ha, and it is selected at the beginning of the run from a list of possible places. Each place has different probabilities of being selected for the Ha according to its age ranges.
- **E**: The location defined as "leisure" represents a place usually visited by people routinely and is shared by several Has. Examples of these locations can include cinemas, parks, or shopping centers. There is a list of locations with an associated probability, which varies according to the habits of the inhabitants in each neighborhood.
- **O**: Those defined as "other locations" are less frequent. As examples, ATMs, warehouses, restaurants, supermarkets, pharmacies, and public transportation can be included.

Time slots and age ranges are defined as presented in Table 4.

Table 4: Time slots and age ranges defined in AbCSim

Time slot number	**Day time**	**Age range number**	**Age range name**	**Years old**
0	8:00 to 11:59	**0**	Children	0–14
1	12:00 to 15:59	**1**	Young people	15–24
2	16:00 to 19:59	**2**	Adults	25–39
3	20:00 to 23:59	**3**	Older adults	49–64
		4	Elderly people	Over 65

As an example, Table 5 shows matrix values $A_{h,e,l}$ for the HMM of specific neighborhood l for age range 0 (*children*) and time slot 0 (*morning*). Therefore, $a_{0,0,1}(i, j)$ has the probabilities that a child (e = 0) in neighborhood l during the morning (h = 0) moves from state *i* (row) y to state *j* (column). In particular, $a_{0,0,l}$ (1, 2) = 25 is the probability value (multiplied by 1000) that a child from neighborhood l within time slot 0 leaves work/study (1) and goes to a leisure location (2). **Appendix D** presents probabilities in matrices A and B for all age ranges, time slots and neighborhoods defined in AbCSim for the different phases of the Preventive and Mandatory Social Isolation (PMSI) indicated by the Argentine National Government. All HMM parameter values were proposed using expert knowledge and field surveys and corroborated with Google Mobility® records.

Table 5: Matrix values A for HMM for age range 0, time slot 0 for human agents in neighborhood l of the city (in probabilities, multiplied by 1000, that Ha "leaves" one location and "goes" to another location).

		Goes			
		Home	Work/ Study	Leisure	Others
Leaves	Home	50	875	25	50
	Work/Study	25	900	25	50
	Leisure	25	900	25	50
	Others	25	900	25	50

2.4.3.1. Infectious Trail Sub-model

This sub-model represents the possibility of a Ha becoming infected due to contact with surfaces previously contaminated by another Ha. According to some studies [63], [64], the most common everyday materials prone to human contact are plastics. There, the virus can last for a time that depends exponentially and inversely on the ambient temperature. If an infected Ha remains in a given location for longer than 16 minutes, it is possible that they leave an infectious trail on the handled objects (fomites). This trail can be mathematically modeled [63] as:

$$P(t) = e^{((-b).t)}$$

where b is:

$$b = e^{\left(-(4.9)+\left(\frac{temp}{10}\right)\right)}$$

Here, *P(t)* represents the probability of being in contact with the virus through a plastic surface; *t* is the time elapsed since the fomite was handled, in hours, and *temp* is the daily mean temperature. This formula was implemented in the GIS projection system, making each cell where an infected Ha remained able to infect another Ha with the corresponding probability *P(t)*.

This factor has been included for model completeness reasons since it is related to several hygiene measures adopted for the prevention of this disease. In practice, and in most recent literature, it has been shown that this factor has no significant impact [65], [66].

2.5. Obtaining and adapting AbCSim parameters

As described in the previous sections, the model consists of different blocks and sub-models, each of which has its own characteristic parameters that need to be adjusted for correct functioning.

Due to the heterogeneous nature of AbCSim, each sub-model uses different mechanisms to obtain, adjust and adapt parameters. Some of the constants were obtained directly from the literature, while others were adjusted using the grid search method and comparing simulation outputs with available real data such as Google Mobility® and other governmental and open repositories such as the Entre Ríos province Critical Units Monitoring Program (*Programa de Monitoreo de Unidades Críticas*, PMUC). These public state programs were supplied with data generated by the population of Paraná city, province of Entre Ríos. The city of Paraná has 270,968 inhabitants, and the data provided to the research group were completely anonymized and de-identified, so an equal proportion of men and women was assumed.

Lastly, because the model represents many aspects of reality through different parameters in an explicit way, the information obtained here was assessed ad hoc, and the parameters were adjusted by an expert.

The particularities of each block are described below, and **Appendix D** details the main parameters of the model, along with a preliminary sensitivity analysis, to facilitate reproducibility.

2.5.1. Block of Within Host Progression

Based on the values proposed in the literature [42], an initial calibration of parameters linked primarily to virus spread in the hosts was generated. To adjust the parameters values of virus spread in the host, information on the evolution of epidemic variables from March to May 2020 in the municipality of Vo (a small village in northern Italy) [67] was used as well as the geographical, climatic, demographic and habit data for its citizens[7].

The initial conditions and parameters related to host transmission in the city of Hoyo de Manzanares were applied to validate the model[8]. In this case, by following the methodology presented by other epidemiological models based on agents [9], [68], it was verified that the AbCSim outputs are consistent with data collected in the field and that the model output dispersion, measured in terms of the interquartile range, is acceptable.

Lastly, a simulation was run with actual data obtained from the district of Loncopué, Neuquén province, to test the model against habits verified for Argentine cities[9]. For this implementation, not only local habits were considered but also a phase change of PMSI. Since the reported daily case data for this city are compatible with the model outputs, this information can be used as a measure of AbCSim validity, thus defining the values presented in Table 3.

2.5.2. Between-Host Transmission Block

The mask and distancing values in the *interpersonal contact* sub-model were set in agreement with the literature presented in Section 2.4.1. As the isolation and distancing phases changed, the increase in people's mobility was verified, which was reflected in the information

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[7] https://www.google.com/maps/place/35030+Vo',+Padua,+Italia/@45.3302273,11.6410366,1228m/data=!3m1!1e3!4m5!3m4!1s0x477f21b5a67dbbe9:0x407098715916650!8m2!3d45.3220524!4d11.6500219

[8] https://comunidadmadrid.maps.arcgis.com/apps/PublicInformation/index.html?appid=cdfb61b3eb3a49c2b990b4fdb41dfcfe&fbclid=IwAR1LGWldM48rEcPXA9EouUaKip_B756HsY0NLRVHKKyLMO0XVs1LXVZYGz0

[9] https://www.clarin.com/sociedad/coronavirus-argentina-loncopue-pueblo-asado-propago-enfermedad_0_t7IEWiIT6.html
https://www.lanacion.com.ar/sociedad/coronavirus-neuquen-aisla-loncopue-pueblo-donde-se-nid2352684/

provided by Google Mobility[10] and presented in **Appendix D**. The change in people's mobility toward the activities of normal pre-pandemic life is reflected in the changes in parameters of matrices A and B of various HMMs also presented in **Appendix D.**

3. RESULTS

This section presents the simulation output results obtained with AbCSim, with the data and adjustment of the parameters corresponding to the city under study, from June 12, 2020, when local cases began rising most significantly, through December 30, 2020. The model was fed with the city climate graph, changes in isolation/distancing phases, and the initial number of infected people corresponding to this period.

Figure 5 shows the comparison between the number of ICU beds occupied by COVID-19-positive patients, as obtained from the PMUC, during the period under study, and the estimate obtained by the model.

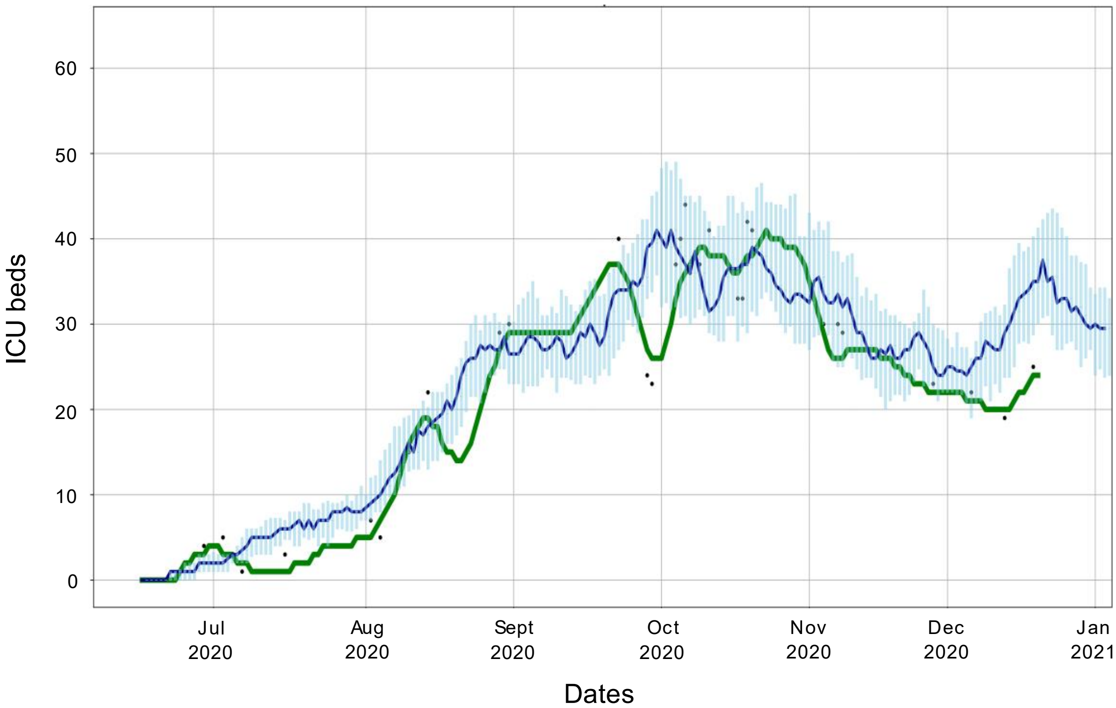

Figure 5: ICU beds occupied by COVID-19-positive patients for Paraná city during the period under study. Black dots show ICU beds for COVID-19+ surveyed by the Critical Units Monitoring Program of Entre Ríos province; green show the data interpolation; light blue show the dispersion of the corresponding model output; and blue show its central tendency.

Figure 6 shows the number of people who recovered from COVID-19 during the studied period.

Lastly, Figure 7 shows the accumulated number of deaths from COVID-19 as estimated by the model for the period under study.

[10] https://www.google.com/COVID19/mobility/

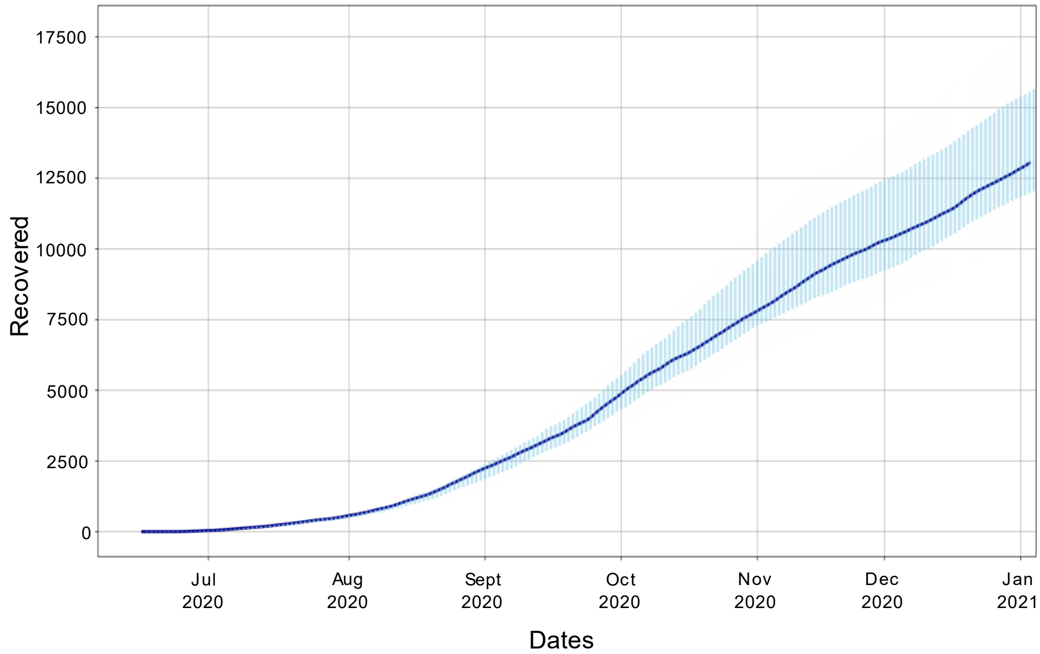

Figure 6: Accumulated number of people recovered for Paraná city estimated by the model in the period under study. Light blue shows the dispersion of the model output, and blue shows its central tendency.

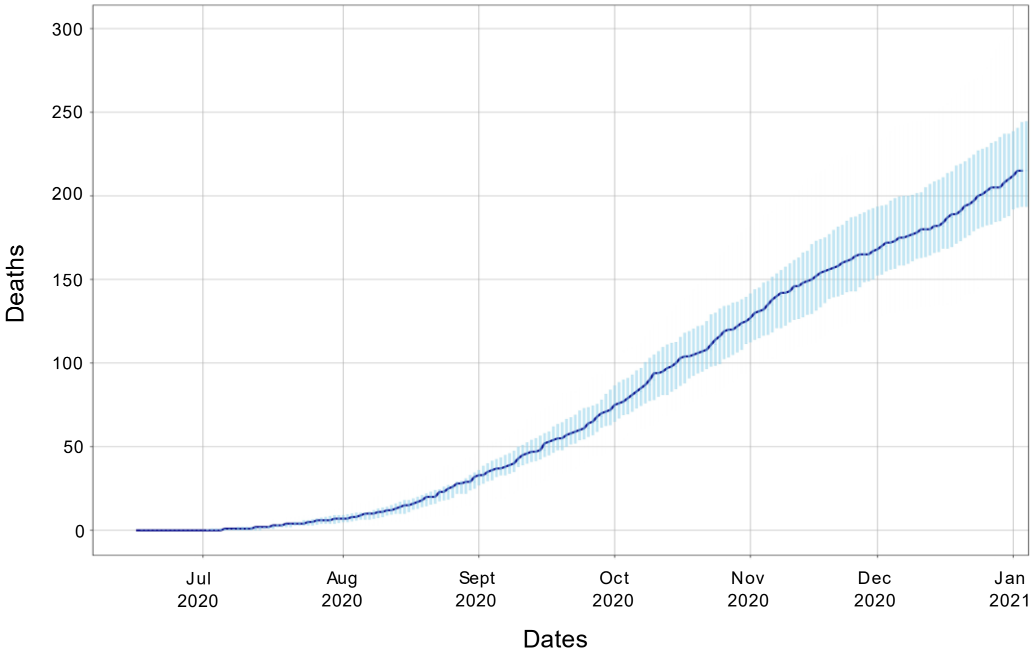

Figure 7: Accumulated number of deaths due to COVID-19 for Paraná city as estimated by the model during the period under study. Light blue shows the dispersion of the model output, and blue shows its central tendency.

4. DISCUSSION

The results presented in the previous section demonstrate the validity of the model's predictions for this case study. For example, Figure 5 confirms that the weekly ICU bed occupancy reports on COVID-19 patients are compatible with the output values of the model.

sinc(i) Research Institute for Signals, Systems and Computational Intelligence (sinc.unl.edu.ar)
Carlos M. Pais, M. Godano, E. Juarez, A. Del Prado, J. Biurrun & H. L. Rufiner; "City-scale model for COVID-19 epidemiology with mobility and social activities represented by a set of hidden Markov models"
Computers in Biology and Medicine, Vol. 160, 2023.

Moreover, the model's output accurately follows the real evolution of this variable, predicting that toward the end of December 2020, the number of occupied ICU beds would decrease again after an increase during mid-December. This fact was verified by ad hoc local official data collected in the field by PMUC. This observation shows that AbCSim is a reliable tool that can be used as a predictor of ICU bed occupancy in the short term. This information is extremely important for anticipating possible local health care system strain.

The model estimates that the number of infected people is much higher than official reports show, which is consistent with the literature from other case studies [10], [15]. This fact also makes it impossible to contrast the number of people the model predicted as recovered cases (Figure 6) with the field data. This impossibility is due to the convergence in infected persons' output of cured and dead Has from symptomatic and asymptomatic compartments.

The cumulative number of deaths estimated by the model shown in Figure 7 is directly comparable with the numbers reported by the UTN FRCU - COVID-19 GIBD Research Group Databases for the city of Paraná[11], showing very good coincidence.

All these results have been obtained for the city of Paraná. However, the model can be tailored to any city, village or neighborhood, implementing the corresponding GIS layer as described in **Appendix C**. As already mentioned, in [40], AbCSim was successfully applied to the city of La Rioja, also in Argentina. In that case, local authorities used it to predict, based on different possible scenarios, the increase in ICU bed occupancy after the end-of-year holidays.

In addition, it is also possible to run the model structure in parallel for the different cities, each of which has its own corresponding GIS layers, climate, demographic data, comorbidities, social customs, etc. Following this idea, the model was also used in a broader study to simulate 3 complete provinces of the Argentine Republic (not yet published). Many "island-type" models were created, because there are cities and towns in each provincial state, and then coupled by exchanging the corresponding percentage of Has. This geographic ensemble of different implementations of the model made it possible to simulate the evolution of COVID-19 for a society of more than 5 million people with similar results as the ones presented here.

It is important to note that hardware resource requirements grow exponentially with the number of instantiated Has and linearly with the number of Markov matrix changes. This trend indicates that although this modeling strategy allows more realistic results to be obtained and adjusted to certain local contexts, it comes at a higher computational cost than other classical strategies. For example, it is possible to compare the number of parameters of a global mathematical SEIR model for COVID-19 (similar to the one used in Section 2.3.1) with respect to the set of parameters used by AbCSim in this work to simulate a PMSI period. For this type of SEIR model with a single age range, only 8 parameters are needed, which contrasts sharply with the

[11] https://gibd.github.io/covid/Entre-Rios.html

712 parameters in the AbCSim model (7 infectivity parameters + 2 interpersonal contact parameters + 702 mobility parameters + 2 infectious trait parameters).

The use of Markov models for modeling agent mobility has yielded good results for this application, allowing us to summarize in relatively few parameters the local characteristics of the population in the different parts of the city. The simple and straightforward interpretation of the transition matrices has made it possible to adjust the values according to the different isolation/distance phases and to contrast the results with real data extracted from Google Mobility. This model is a valid alternative to agenda-based methods, which lack rigorous mathematical foundations because of their heuristic approaches.

In this work, the changes in social activities and contacts throughout 2020 motivated by PMSI, or those related to alterations in social mood, were implemented by directly modifying the Markov matrices of the agents. However, it is also possible to explicitly consider the agents' ability to adapt and learn from different conditions, moving from a model with “silly”/“passive” agents to a model with “intelligent”/“reactive” agents.

Direct comparison of the results obtained with those of other ABM models is not possible because no results from other authors have been reported for this location. The large variability in terms of complexity, for example, in the number of parameters and agents, also makes a fair comparison difficult. Moreover, in most of the published studies, the analysis of the results is of a qualitative type or a relative comparison between different scenarios. See, for example, the results reported in [6], [9], [10], [33], [34]. In taking all these aspects into account, it can be said that the results obtained in this work are comparable or in some cases even better than those reported in the specific literature.

5. LIMITATIONS

One of the main limitations is related to obtaining sufficiently detailed official epidemiological data, such as local symptomatic and asymptomatic cases. In general, this issue depends on the particular policy of access to public information in each place and the reliability of the data obtained.

The methodology of the local health system to obtain the evolution of ICU bed occupancy and deaths was correct. This information allowed the group of researchers to have sufficient data for validation continuously, as soon as the investigation required it, and thus to maintain the model validation. However, the same pattern did not occur with the number of reported daily cases due to the poor testing methodology. Therefore, the number of daily COVID-19 cases (symptomatic and asymptomatic) estimated by the model during the period under analysis is not shown in the Results because in Argentina, official reports are highly dependent on erratic testing policies and insufficient case monitoring, apart from the difficulty in detecting asymptomatic cases.

6. CONCLUSIONS

This work presents an agent-based model called AbCSim, which is capable of reproducing the evolution of the COVID-19 epidemic at a local city scale. The model explicitly incorporates various aspects of the epidemic, which facilitates its adjustment to different case studies.

The methodology used to adjust the system's parameters is provided as well as the methodology to consider changes in social distancing measures, in people's activity and climate variations over time. As a case study, the model was applied to Paraná city during the second half of 2020.

The results obtained here are consistent with those reported by different official sources, such as PMUC, in particular with the number of ICU beds for COVID-19 patients in the city. It was also verified that the model outputs are consistent with the number of deceased people reported for the period under consideration. It can be concluded that the model can be used to predict the most likely evolution of the number of cases and the number of beds to be occupied in the short term.

AbCSim provides information that can be used to quantify the effects of implementing different health policies at the local level. These features make this model a useful tool for decision-making with the goal of assessing the use of the health care system and preventing it from collapsing while including a contextualization of people in their local economic and social environment. Future studies will present several case studies in this regard, including the results of applying this model to other cities or even at the state scale. The extension of this model to considering the effect of vaccination campaigns and different virus variants will also be presented.

Acknowledgments

The field surveys were approved by the CEYSTE Ethics Committee (CONICET, Argentina), who verified that the structure, anonymization, and informed consent were correct before field implementation.

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Conflict of interest

The authors have no conflicts of interest to declare.

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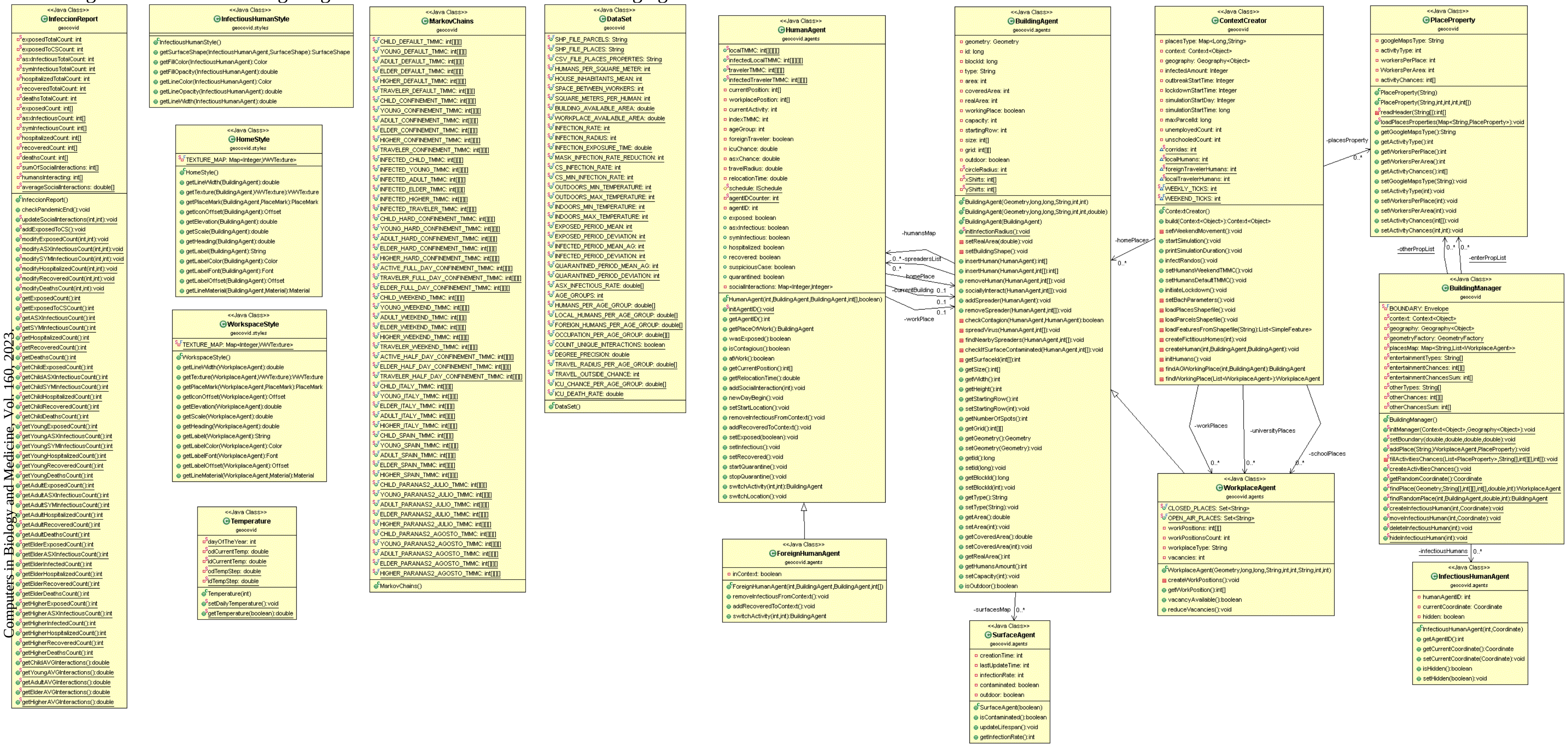
Appendix A: AbCSim UML digram

The following graph presents the UML diagram of AbCSim with all Java classes implemented in Repast. All methods and attributes are shown. For Paraná City, the number of HumanAgent instances at the begining of the run is of 270.968 and BuildingAgent is 67.793.



Appendix B: Detailed ODD protocol description of the model for Paraná city

Introduction

To generate a detailed description of the model, the guidelines proposed by the ODD (Overview, Development and Design considerations) protocol are followed.

Purpose

Help the local healthcare system decision-makers avoid system saturation by predicting the number of intensive care beds that would be occupied by Covid-19 patients.

Specific objectives:

- Represent those behaviors, interpersonal relationships and customs of the people belonging to the city of Paraná, which are interesting from the Covid-19 epidemiological point of view.
- Include in the dynamics of the disease the variables linked to the geography and climatology of the area under study.
- Obtain a set of output variables that allow predicting, at the local level, the occupation of ICU beds by Covid-19 patients and the daily number of patients and deaths by Covid-19.
- Serve as a support tool for meso-management decision-makers to cope with the Covid-19 epidemic.

Entities, variables and scales.

Being an agent-based model, a fundamental part of the system consists of the implementation of human agents (Ha), which possess specific characteristics and attributes of risk factors and comorbidities (Epidemiological Characterization submodel). In addition, they can contract and transmit the virus, change their health status and symptoms, and modify their behavior accordingly (Infectivity submodel). Also, the relationship between the different human agents with each other and with the environment is represented, since the distance between the agents, the use of the mask, the respect for the place´s capacity and the different rules and protocols play a key role in modeling the transmission of the virus (Interpersonal Contact submodel).
Each agent has a behavior according to his age range, habits and the neighborhood where he lives, which are randomly assigned at the beginning of the simulation according to the population statistics of the city of Paraná.
The mobility of each agent is linked to the matrices of change of states (activities/places) implemented by means of Hidden Markov Models (HMM). Each of the HMMs corresponds to an area where the agent lives, the age range to which it belongs and the time zone in which it is, at the time of the simulation.

Agents

The most important entities are the **human agents (Ha)** since, as mentioned above, this is a one-to-one model and therefore there are as many Ha as people in the geographical area under study. Therefore, Ha is a class of objects of which there are 276.975 instances.
Each of these agents has the following list of attributes and methods:

Attributes:
- Pointers to the current context and parcel, workplace and home.
- Index of the neighborhood/section it belongs to
- Markov state index where he/she is (0 is home, 1 is work/study, 2 is leisure, 3 is other).
- Age group to which you belong
- Last position and last time in which you changed status
- Scheduled activities
- Unique identifier
- Map of daily contacts
- Status (Contagious, Infectious asymptomatic, Infectious symptomatic, Hospitalized in ICU or Recovered)
- Booleans that indicate if the patient is isolated by symptomatic or preventive quarantine, if he/she respects social distancing, if he/she was affected by aerosol in the current plot and if he/she was in close contact with symptomatic.
- Risk factor for comorbidity.

Methods:
- Constructors
- Getters that return attribute values
- Generation of close contacts
- Respect for sanitary measures
- Modification of the number of social interactions
- Movements through the plots
- Exposure and contagion
- Beginning of the infectious period and definition of the duration and severity of the disease
- Recovery or death
- Changes in status
- Compliance with quarantine
- Changes in activity

Foreign agent (ExtrAgent): it is an extension of the human agent with the particularity that it can enter and leave the subcontext. It has the same methods and attributes as a human agent, but a Boolean is added to determine if it is inside the subcontext and methods to add or remove it from the subcontext.

InfectiousHumanAgent: This class is used to represent in the map the location of the infected agents, containing lists with identifiers and locations.

Building (BuildingAgent): it is the basic class of the plots. It contains attributes such as pointers to the subcontext, type of section, coordinates, area, capacity, etc. It also contains a list of the agents that are currently present in the plot and the infected agents and infected surfaces within the plot. In addition to constructors, it has methods to calculate the radius of contagion by droplet and aerosol, evaluate the occupiable area, insert humans in a given position and estimate the displacement of the agents, search for contacts, set contagions, estimate the infectious trail and modify and return its attributes. The **agent's home** is an extension of the BuildingAgent class that inherits its methods and attributes but also has a list of the occupants of the house, being able to add and remove members and has methods for quarantining its members.

Workplaces, which represent the plots where Ha work or study, is an extension of the BuildingAgent class that inherits its methods and attributes and incorporates methods to determine close contacts and evaluate contagions, considering measures such as use of masks, which are modified according to public policies. The same class extends to

public transportation and schools, which have methods to ensure compliance with established protocols.
Finally, **SurfaceAgent** is a class that represents the phomite or contaminated surface, which contains a method to calculate the viral load, which is affected by the time course and the cleanliness of the facility.

Context

The context is made up of the positions occupied by each agent and each plot, with its type or utility. It also gathers information on the socio-sanitary measures of each location. This block will be described in more detail in the Location Sub-model.

System variables

The set of variables that affect more than one agent and/or the environment are the following:
- Temperature: average daily temperature, loaded in an input vector.
- Markov matrix: set of matrices that have the probability of changing the state and activity of each agent. These matrices are updated every two weeks or whenever a mandatory social distance phase change is determined. The calculation and updating of this set of variables is described in more detail in the Mobility/Activity Sub-model.
- Time: the current time is calculated on each tick, given that the time range in which the calculations are being made is defined according to the value of this variable.

There are also variables such as the number of instantaneous and accumulated symptomatic and asymptomatic infected, recovered, hospitalized and deceased Ha agents, and a set of interesting variables for obtaining global results in the system.

Scales

All variables and attributes of the different agents are updated every one tick, which corresponds to 20 minutes, and it is assumed that the epidemiological dynamic evolves only during 12 daytime hours. The full run covers a total of 196 days, as it runs from 1 July 2020 to 8 October 2021.
The highest spatial resolution is given by the surface of an average plot, where an average plot is defined as an area equivalent to a 30x10 mts2 housing unit.

Clusters

Parcels where a group of more than 20 agents converge have a special impact on the dynamics of the epidemic and therefore, some of these have been treated with their specific programming. Among these groupings are: School; Party; Club; Gymnasium and Stadium.
Public transport is a cluster with a particular impact on the model results and will therefore be discussed in Transport Sub-model.

General process and timing

The whole process is dominated by the calculation of the next position of each agent.
At each tick, all Ha agents are selected. In random order (by uniform distribution), one by one, the entire list of available Ha is scrolled through and moved to its next position. To change the position of each Ha, the corresponding cell in the corresponding Markov Matrix is identified (according to the time, its age range and neighborhood) and,

depending on the result of the call to the Plan_Move method, the agent is placed in the new position.
Once placed in its next position, its attributes and methods linked to the disease are calculated (if it is in the Latent state, for example, its time counter is increased by one and it is checked if the time established to pass to the Symptomatic/Asymptomatic state has been exceeded). The same happens with the rest of the variables linked to the disease, including the Immunisation_Time, for example.
Depending on the value of some attributes of the agent, such as its level of adherence to the place's capacities or aphores (Aphore_adherence), for example, the movement is validated or discarded.
This process, which can be defined as an asynchronous update, is repeated as many times as Ha exist for each tick or time unit.

Design

General outline of the model

As already introduced, the model is implemented in Java and runs on Repast, which is an advanced, free and open-source agent-based modeling and simulation platform. It is multi-platform and allows the implementation of the characteristics, behavior and interaction of agents with each other and their environments. The design takes into account the complexity of the dynamics of the pathology itself, together with the interpersonal relationships of individuals, their habits, access to health services, mobility and adherence to Covid-19-related care arrangements (use of masks, distancing, aphores adherence, etc.). Geographical and climatological information is also taken into account as determinants of the dynamics of the epidemic.
Figure B.1 shows the general diagram of the model, identifying its different blocks and levels of implementation. The top-level shows the model in its most abstract stage, as a black box, indicating the initial conditions, inputs and outputs. The intermediate level shows the two main blocks that make up the model: one block dedicated to the simulation of the spread of the virus within each host and another dedicated to the transmission of the disease between hosts. Finally, at the lower level, the different sub-models are indicated with their own parameters (Infectivity, Epidemiological characterization, Interpersonal contact, Location and Mobility/Activity, Transport and Infectious trail). In the following sections, they will be properly characterized and detailed (together with their contributing modules).

Adaptation, learning and emergent phenomena

The model does not foresee any learning phenomena whereby agents change any of their methods in pursuit of a particular goal.
However, as the simulation time elapses, a number of agents will have their Aphore_adherence attribute changed. This adaptation means that as time goes by, the values of the number of agents in the different plots linked to leisure, work and recreation have a greater number of agents.
On the other hand, with each change in the mandatory social distance phase or with each significant change in the mobility of people, the Markov Matrices are updated, which results in an adaptation of the whole system to the changing mobility conditions.

Stochasticity

Given the stochastic nature of the epidemiological phenomenon, some of the variables (like climate predictions) and the model with which we try to reproduce it, several "complete" runs must be carried out to obtain the results, requiring the use of a computer cluster. This tool is used to test different scenarios of the model, running each scenario as many times as it is possible to obtain the central trends with logical dispersions.

Sensing and interaction between agents.

Each Ha, before being mobilized to a new position, senses whether it is outside the grid of its city. If it is mobilized to a position outside the grid, it is returned to its Home position at the end of the 12 hours of the day. When this happens its set of attributes are updated according to the infection probabilities defined by the cities surrounding its locality.
In addition, each agent senses whether the plot to which it is mobilized is not over capacity. If this is verified, the agent does not change position.
If the agent in the Susceptible state is within 1.8 meters of an agent in the Infected state (symptomatic, asymptomatic or hospitalized) for 2 ticks or more, it may move to the Latent state (mediated by the joint probabilities β and Mask_use).
This latter sensing behavior is described in more depth in Host-to-host transmission block.

External observation of the system

During the entire run, in each tick, the system generates vectors that compile the number of agents in each state, as well as an accumulation of hospitalizations and deaths.

Initialization

At the beginning of the simulation, the entire environment is defined, with the set of plots dedicated to shops, public transport, squares, and other places for housing, work, leisure, and others.
Also defined are all the Ha (one for each inhabitant of the city) with their different attributes. Of all this set of agents, only 1 has its attribute State in Symptomatic.
The Markov Matrices have the transition and emission probabilities defined for the first phase of government mandatory social distance.
The whole set of parameters linked to the disease itself is also defined (probability of admission to the ICU, probability of transition to Recovered, probability of death, etc.) in Table B1, which has all these values.

Input Data

The input data consists of the following list of values and vectors:
- Number of human agents, with a given age distribution and risk associated with comorbidities.
- Georeferenced plot information
- Population habits, characterized by age range and socio-economic level.
- Climate information
- Information on circulating variants

- Information with socio-health policies
- Daily immunizations for each age group in each sub-context and proportion of vaccines given
- Initial infected

Sub-models

The different blocks presented in Figure B1 represent the sub-models into which the model has been divided for ease of understanding. Each of the sub-models developed are presented below.

In-host virus propagation block

Infectivity Sub-model

The infectivity sub-model emerged from a mathematical model proposed by Arenas et al. [2] which was adapted for the model itself and the properties of the platform used to become the method that represents the process of virus spread within human agents.
Each agent has an attribute indicating which of the seven possible states it is in (S: susceptible; E: latent or exposed; I: symptomatic infectious; A: asymptomatic or mildly symptomatic infectious; R: recovered; D: dead; and H: hospitalized).

Basically, susceptible agents become infected with a probability $\boldsymbol{\beta}$ after close contact with another infected agent (whether symptomatic or not). This probability of infection depends on the average daily temperature (represented by the variable v). If the susceptible individual (S) becomes infected, he/she becomes part of the pool of people exposed to the virus (E).
Individuals exposed after $1/\alpha$ days become symptomatic or asymptomatic, depending on a probability η, which adjusts for the age range in which the agent is found. Once infected, there are two possible scenarios: the agent may require hospitalization (H) in a therapy or intensive care unit (ICU onwards) or the agent may become recovered and not re-infected (for a p
The implementation of this block allows the behavior of the agents to change according to the epidemiological state in which it is found, for example, if it is susceptible, the agent follows the pre-established mobility patterns. However, when they become exposed, this changes, they stop moving and quarantine themselves at home (which implies that the agents they live with are also exposed).
The probability of contagion does not depend exclusively on contact with other agents but is also affected by environmental variables such as ventilation and climatic values, as Covid-19 is a seasonal pathology [3], [4], [5]. Therefore, $\boldsymbol{\beta}$ must be modulated by the mean daily temperature. For this purpose, $\boldsymbol{\beta}$ is multiplied by v, a variable dependent on the daily mean temperature, which reaches its maximum (value 1) on the coldest day of the year and its minimum value (0.5) on the hottest day of the summer.

Epidemiological characterization sub-model.

Each agent has attributes that modify the spread parameters in Table B1, such as the existence of co-morbidities or cohabitation with a symptomatic infected person.

Comorbidities increase the probability $\boldsymbol{\gamma}$ of passage from infected to ICU inpatient according to the percentage value presented in Table B2 [6], [7], [8].

Table B2: Increase in the probability Y of going from infected to hospitalized in ICU, according to the co-morbidity that Ha has.

Pathology	Increased probability of admission to ICU
Asthma	0,1230
COPD	0,1230
Diabetes	0,3100
Hypertension	0,2889
Obesity	0,5863

Additionally, each agent has two other attributes that denote how their behavior with respect to epidemiological protocols affects the probability of infection, these are the respect for social distance (and capacity in commercial premises), and the use of masks. As an example, if the agent has a high tendency to wear a mask, beta is reduced by 30% [9].
On the other hand, the distance attribute is Boolean (high or low). If it takes the value high, when an agent is about to change location according to the mobility matrices, before making the change, it verifies that the space (in square meters) in the building allows separation of at least 1.80 meters with the other agents present in that space at the same instant. If this condition is not met, the agent remains where it was instead of making the transition. Whereas, if the distance attribute is low, the agent makes the change of location according to the mobility matrices without any prior control with respect to the place´s capacity.

Host-to-host transmission block

This block considers the different forms of virus transmission (infectious trail, direct contact, or droplet-to-droplet) between hosts in different spaces (home, office, recreation, public transport), and their specific circumstances (capacity, ventilation, temperature).

Interpersonal contact sub-model

Each agent has a method that allows it to calculate if there is another agent within two meters of it, if this is true for a period of 15 minutes then close contact is considered to have occurred. As this contact condition is true, if one of the two agents is in an infected state (either symptomatic or not), the other modifies its epidemiological state attribute to exposed E, mediated by the probability $v(Temp)*\boldsymbol{\beta}$. In addition, if an agent has symptomatic infected status, all those living together in the same dwelling automatically switch to exposed status.

Location sub-model

For the Location sub-model, a specific GIS module specific to the Repast platform is used to differentiate and characterize dwellings, offices, shops, schools, squares, means of transport and other relevant places where individuals stay.
The GIS layer was created by first incorporating a layer with a satellite image of Paraná in QGIS, then SHAPE files were generated where polygons were used to delimit the different neighborhoods, identified as sections based on the available land registry information. Scripts were run (detailed in Appendix C) to delimit the dwellings, then another layer was generated with a shape file with this information.
Subsequently, the presence of offices and commercial premises in the area was analyzed, based on the information that Google Places® has for these spatial coordinates. In addition, squares, churches, hospitals and schools were incorporated into the corresponding location.
A new shape file was then generated with all the cleaned information in a new layer, including coordinates, type of business and capacity. Additionally, each of these locations was assigned the corresponding Markov model state output type (Figure B3) and saved in the file.

Public Transport

This block is responsible for representing the effect of public transport on contagion rates. Although Paraná has an airport, because most flights were canceled due to government regulations, this block is limited to public passenger transport by urban buses.
The buses were represented as fixed locations or positions on the map, where each bus stop is a 10 x 4 m plot. Through each of these plots emulating bus stops, an agent can enter a bus every 20 minutes (representing the frequency of local public transport). On each of these occasions, a number of agents can enter and remain at an average distance of 2 meters for a period of 20 minutes. However, during 1 minute of this time period, the minimum distance is not met (simulating the moment when the passenger is in contact with other individuals from the moment he/she gets on the bus until he/she reaches the corresponding seat).
Once the 20 minutes of the supposed "journey" have elapsed, the agent can either "jump" to another part of the map or remain in place for another journey (of the same duration), at the end of which this disjunction will be revisited. The choice of one alternative or the other depends on a transition probability defined by the Mobility/Activity sub-model which will be discussed in a forward section.
While public transport has its own capacity that attempts to guarantee the 2-meter separation, there is still the possibility of close contact because each agent has the attributes of adherence to wearing a mask and social distance that modify the probability of infection as elsewhere.

Schools

While geographically the schools were charged in the same way as any workplace, the implementation of permanence in these establishments was done in a differentiated way to follow the guidelines and protocols determined by the provincial Education Council. Paraná, like in many Argentinean provinces, implemented a bubble model, which

allows students to maintain distance from each other, but involves alternating periods of face-to-face and virtual classes. This was implemented in the Java code of the model.
It should be clarified that these protocols were implemented since June 2021.

Ventilation

An important factor in the spread of the virus is ventilation [10], [11]. When workspaces and public transport are properly ventilated, allowing air circulation, the infection rate is drastically reduced (the β is halved) thus decreasing the likelihood of infection.
Knowing this information is essential to test different scenarios that allow decision-makers to take action (either tightening or loosening restrictions) based on the projections.
Ventilation is related to location, as in the implementation different methods were created for ventilation in homes, offices, public transport and entertainment spaces respectively. This allows adapting the parameter for different dates, as in public transport, offices and recreational spaces ventilation is regulated by existing protocols. In homes, ventilation tends to be present in spring and autumn. However, in summer and winter, when temperatures reach their extremes, a decrease in ventilation is observed (due to home air conditioning strategies, such as the use of cookers and air conditioners).

Mobility/Activity submodel

This sub-model is used to simulate the mobility or displacement of individuals living in a section or neighborhood of the model, according to the age range to which they belong and the time slot being simulated. It makes it possible to establish which activity the agent is going to carry out in the corresponding location at the following instant of time. Each activity has a different probability of duration and location.
In order to calculate the position of an agent at a given time, a Hidden Markov Model (HMM) is used that defines the probability of moving from one location to another, based on the position at the previous instant and its own attributes.
Mobility behavior varies according to the time of day, whether it is a working day or a weekend, the age range, and the type of neighborhood.
In this model, it is considered that contagion on public roads is negligible and that there is no transmission during the period of time in which an agent moves from one place to another, except in the case of traveling by public transport, which is considered an activity and follows the guidelines explained in the previous section.

The set of the HMMs that make up the Mobility sub-model is defined as $h_{,e,l}$ (A,B,π). According to the timetable (h), age range (e) and neighborhood or zone to which it belongs (l), each agent uses a specific HMM. Each one has 4 possible states that represent a type of activity: Home (C), Work (T), Leisure (E) and Other (O).
Each HMM has its own transition matrix $A_{h,e,l}$ representing the probability of state change (moving from one place to another), its output matrix $B_{h,e,l}$ indicating the probabilities of occupying a specific place in each state, and π its vector of probabilities of initial locations (which is always (1,0,0,0,0) for the beginning of the day, since it is assumed that all citizens start the day at home). A schematic of the Markov model described is shown in Figure B3.

Each state has its own characteristics: C represents the agents' home, whose geographic location is an attribute that is randomly chosen from all livable locations that are pre-loaded and assigned to the agent during initialization. It has only one possible output.
The state T represents the place of work or study of each agent, is randomly selected during initialization from a list of possible locations (considering that some locations are weighted more heavily for some age ranges) and is kept constant throughout the simulation. It can be shared by different agents. For agents who do not study or work, this location coincides with C.
State E represents a place of recreation that the agent visits regularly and, like T, can be shared among several agents. These can be indoor places such as a gymnasium or outdoor places such as a square. There is a list of places with their associated probability that varies according to the habits of the inhabitants of each section.
State O represents other places that are visited less frequently such as ATMs, restaurants, supermarkets, pharmacies and public transport.

The time slots of the day are defined as:

- Morning: 8:00 -12:00, time slot 0;
- Siesta: 12:00 - 16:00, time slot 1;
- Afternoon: 16:00 - 20:00, time slot 2;
- Night: 20:00 - 24:00, slot 3;
- Evening: 20:00 - 24:00, slot 3.

Appendix C contains all matrices used in the model.
The mobility of agents is also affected by the restrictions imposed by the provincial government, which is also reflected in the mobility matrices. To obtain this information, data from official bulletins were combined with data provided by Google Mobility.

The Infectious Trail sub-model

This sub-model represents the possibility of infection of an agent from contact with surfaces previously contaminated by another agent. It is known from the literature that plastic is one of the most commonly used materials by individuals, and the virus can remain on it for a period that is exponentially and inversely related to the ambient temperature [4], [5]. If an agent with an infected epidemiological status stays in one place for more than 15 minutes, it can leave an infectious trail on the objects it came into contact with. This factor has been included for reasons of model completeness since it is related to several of the hygiene measures adopted in disease prevention. However, more recent literature has shown that its impact is much less than the factors described above.

Outputs

When running the model, AbCSim generates 7 files (csv format) for each run. In the files, each row presents the output of one day in the simulation and, where appropriate, each column represents an age range.

- The first file contains information on bed occupancy, disaggregated by age range.
- The second file presents deaths by age range.

- The third file contains the number of contacts, classified by age range.
- The fourth file has the number of daily cases.
- The fifth file shows the active cases (also classified by age range).
- The sixth file shows the agents that were infected on public transport.
- Finally, the seventh file is a general report, which contains columns to represent the total number of exposed, infected, asymptomatic infected, symptomatic infected, daily bed occupancy, total number of recovered, hospitalized and deceased.

Obtaining and adapting the parameters.

The model has two sub-models which in turn are composed of different blocks or sub-models. They all contain different parameters initially calculated from literature and available information. However, during the validation process, these were adjusted to bring the output (mainly occupancy of ICU beds and deaths by age range) as close as possible to the data obtained from reality.

Model validation

The work of adapting the values of all the parameters and final debugging of the complete code was made in different steps. Each step took approximately 15 days of work, so that, once this work was completed, we had data from reality that did not yet exist when the adaptation process began. With the field values of the variables ICU bed occupancy and deaths by age range generated during the adaptation process, the system was validated. For this, it was assumed that the results of the simulations were correct as long as the central trends of these outputs corresponding to 24 runs of the model had a maximum deviation of 10% with respect to the values obtained in the field.
In addition, it was verified that the dispersion of the outputs (represented by the interquartile range) was not too wide so that a high percentage of the simulations gave results that exceeded a deterministic criterion. A 90% of occupancy of the available ICU beds in the city was defined as a decisive criterion. Therefore, in order to validate the system, it was verified not only that the central tendency of the simulations was sufficiently consistent with reality, but also that the dispersion of the outputs did not lead to incorrect health decisions.

Appendix C: Generation of GIS layer of the model for Paraná city

Introduction

This document describes the main steps needed to develop the GIS layer of AbCSim model corresponding to Paraná city. It is possible to adapt it to any other city, changing the corresponding data, i.e., the images, number of inhabitants, coordinates, etc.

Step 0: Software installation

As a prerequisite to the generation of the geographic information layer, the installation of a Geographic Information System (GIS) application is required. In this work, QGIS[12] has been used, which is a free and open-source multiplatform software. A Google Cloud account and enabling the Google Places[13] tool are also required. Finally, some scripts must be programmed specifically to automate the various text and data analysis and manipulation tasks. Version 3.6 of the Python language[14] has been used for this work, due to its versatility and popularity. It is also necessary to install the corresponding requirements (Shapely==1.7.1 and pyshp==2.1.3), which can be easily done via a console command.

Step 1: Initialization

A QGIS project is initialized and an XYZ layer is added, Esri Imagery/Satellite[15] is recommended for this task. Once this layer is loaded, the location or region of interest is located and saved (see Fig. xx.1 a). Then another XYZ layer is loaded but using the street view, marking its boundaries. For Paraná city it is possible to use OpenStreetMap specific data[16], find the appropriate relations[17], and then make the corresponding adjustments (see Fig. xx.1 b). Finally, the result is exported using the KML format.

[12] https://qgis.org/en/site/forusers/download.html
[13] https://cloud.google.com/maps-platform/places
[14] https://www.python.org
[15] https://www.spatialbias.com/2018/02/qgis-3.0-xyz-tile-layers/
[16] https://www.openstreetmap.org/relation/2879942
[17] http://overpass-turbo.eu/

Figure A.1: a) Example of image of the first layer of Paraná city (left side), and b) the corresponding layer after several adjustments (right side).

Step 2: Generate household location by neighborhood

First, the empty shapefiles corresponding to the plots must be generated using a custom-made script. Then, a layer is loaded with the shapefile generated in QGIS, setting parameters CRS: WGS 84 - EPSG:4326. In the same layer, single-line polygons should be created, dividing the inhabited part into neighborhoods. It is possible to be guided by cadastral files available online. In each generated polygon the index of the neighborhood is indicated with the number of houses to be created. After this, the layer and the corresponding project are saved in QGIS. Then, the script generated at the beginning of this step is run again to create new parcel files. To check the result, a layer is loaded in QGIS with the new parcel shapefile. The spacing between households can be varied by modifying the corresponding variables.

Step 3: Generate Place search points

Empty shapefiles must be generated by running an ad-hoc script that generates the places_regions file. Then the layer is loaded with the shapefile in QGIS. Polygons are created with a single stroke according to the density of places and a distance attribute is assigned. This is done taking into account that Google places do not return more than 60 places per query, so in central areas of the city a small radius should be set (e.g. 100 meters), and in areas where it is known that there are not a large number of businesses this radius can be expanded to reduce the calculation time. It is recommended to make concentric rings that gradually increase the radius as moving away from the city center. Once the process is finished, it is necessary to save and re-run the script used at the beginning of this step to generate the CSV files for each polygon. To verify the result, it is required to load the CSV files into QGIS as layers and change the scale of the symbology to meters and the size to distance + 7% (ellipsoidal). If there are gaps, new points should be added, or each polygon should be slightly overlapped.

Step 4: Getting places using Google Places APIs

In the folder containing the coordinate files, a new script is executed to find the most prominent locations and generate the corresponding output file with all the results in JSON format.

Step 5: Filter overlapping and possible repeated Places

In the same folder with the output file from the previous step, a new script is run to filter and eliminate possible repeated locations. The output is a CSV file with the basic data to be loaded into Google Maps.

Step 6: Search for missing Places categories

A new script is run to search for locations not found in the previous stages. Before running it is necessary to consider that a type query can be made at most every 30 seconds, in order to avoid being detected as a bot. So, it may take some time to complete the whole process. It is not possible to make other queries to Google from the same IP (mainly to Google Maps) while running this script because of the danger of being banned. It is recommended to use a dedicated IP, alternatively use VPS, or a service like PythonAnywhere[18].

Step 7: Filter Places by Type

Another script must be run to correct all the types of locations that have not been loaded or have been loaded incorrectly. These are usually numerous, and it can take considerable time to perform this task because it must be done partially by hand.

Step 8: Verify the existence of Places types in the Markov output file

The output CSV file from the previous step and the Markov output state matrix file must be copied to the same directory. Then new types are added to the Markov output state file and the type is changed in places to an existing one and non-existing places are removed. Afterward, the places must be filtered again until no unassociated types are returned.

[18] https://www.pythonanywhere.com/

Step 9: Create Places shapefile from CSV

In this step, a script must be run to generate the shapefile. Then the corresponding output is taken and loaded as a layer in QGIS, setting CRS and Encoding parameters. In the end, 6 layers are obtained in QGIS. The places and parcels files generated must be incorporated in a folder with a name that identifies the city, in this case "Parana", and that is contained in the "data" folder of the model.

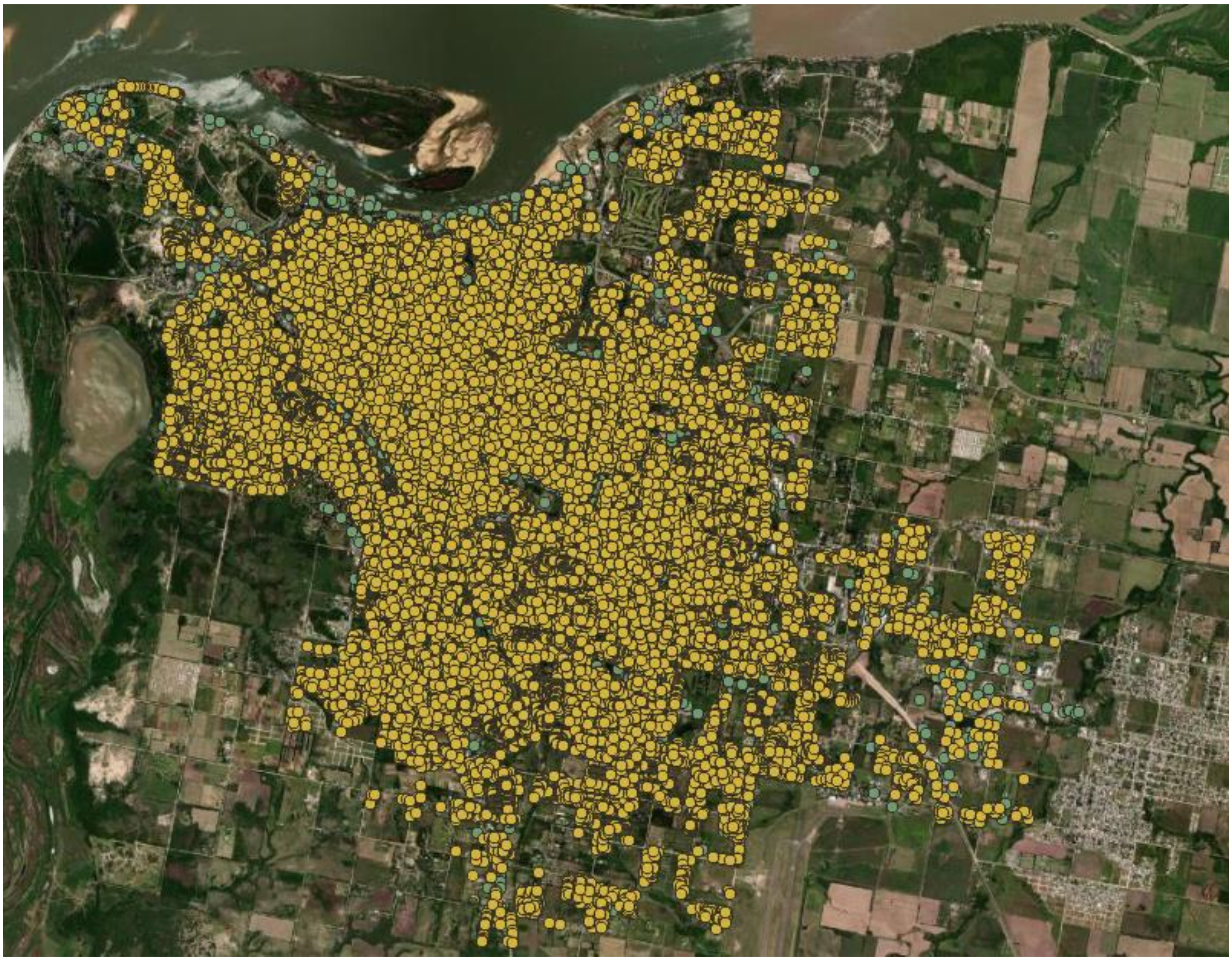


Figure A.2: Example of all-layers superposition for Paraná city.

APPENDIX D

1 State transition matrices of the set of Hidden Markov Models

The values in Table D.1.1 to D.1.5 determine the mobility and activities of the agents according to their age range and neighborhood of residence. In each row, the values related to the representative areas of neighborhoods with a high index of satisfied basic needs (SBNI) are displayed in the left half (Area 2) and those corresponding to neighborhoods with a low SBNI, on the right (Area 11). Given that the behavior of each agent changes according to the time slot and the age range, it is shown how these Markov state transition matrices ($A_{h,e,l}$) change chronologically depending on the changes in people's mobility, which are mainly influenced by the different phases of the Preventive and Mandatory Social Isolation (PMSI) ruled by the Argentine National Government that were verified during the year under study (2020).

FEBRUARY-MARCH-2020 (PRE-PANDEMIC)

	Children-Area 2					**Children-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	75	850	50	25	**Home**	275	650	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	550	250	25	**Home**	150	525	300	25
Work / Study	50	850	75	25	**Work / Study**	50	850	75	25
Leisure	200	350	400	50	**Leisure**	175	325	450	50
Others	200	350	300	150	**Others**	175	325	350	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	550	250	25	**Home**	425	100	375	100

FEBRUARY-MARCH-2020 (PRE-PANDEMIC)

Work / Study	50	850	75	25	**Work / Study**	325	150	225	300
Leisure	200	350	400	50	**Leisure**	475	0	425	100
Others	200	350	300	150	**Others**	425	0	325	250

	Young people-Area 2					**Young people-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	75	850	50	25	**Home**	275	650	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	550	250	25	**Home**	150	525	300	25
Work / Study	50	850	75	25	**Work / Study**	50	850	75	25
Leisure	200	350	400	50	**Leisure**	175	325	450	50
Others	200	350	300	150	**Others**	175	325	350	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	550	250	25	**Home**	425	100	375	100
Work / Study	50	850	75	25	**Work / Study**	325	150	225	300
Leisure	200	350	400	50	**Leisure**	475	0	425	100
Others	200	350	300	150	**Others**	425	0	325	250

	Adults-Area 2					**Adults-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	25	925	25	25	**Home**	225	725	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25

FEBRUARY-MARCH-2020 (PRE-PANDEMIC)

Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	575	200	25	**Home**	175	550	250	25
Work / Study	100	850	25	25	**Work / Study**	100	850	25	25
Leisure	200	675	100	25	**Leisure**	175	650	150	25
Others	200	675	100	25	**Others**	175	650	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	525	150	225	100	**Home**	450	150	300	100
Work / Study	225	250	225	300	**Work / Study**	225	250	225	300
Leisure	575	100	225	100	**Leisure**	500	100	300	100
Others	525	0	225	250	**Others**	450	0	300	250

	Older Adults-Area 2					Older Adults-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	25	925	25	25	**Home**	225	725	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	575	200	25	**Home**	175	550	250	25
Work / Study	100	850	25	25	**Work / Study**	100	850	25	25
Leisure	200	675	100	25	**Leisure**	175	650	150	25
Others	200	675	100	25	**Others**	175	650	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	525	150	225	100	**Home**	450	150	300	100
Work / Study	225	250	225	300	**Work / Study**	225	250	225	300
Leisure	575	100	225	100	**Leisure**	500	100	300	100
Others	525	0	225	250	**Others**	450	0	300	250

	Elderly people-Area 2					Elderly people-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	700	0	125	175	**Home**	750	0	75	175
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	700	0	125	175	**Leisure**	750	0	75	175
Others	700	0	125	175	**Others**	750	0	75	175
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	925	0	50	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	75	75	**Leisure**	825	0	100	75
Others	850	0	75	75	**Others**	825	0	100	75
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	800	0	175	25	**Home**	750	0	225	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	700	0	300	0	**Leisure**	650	0	350	0
Others	700	0	0	300	**Others**	650	0	50	300
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	940	0	35	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	950	0	25	25	**Leisure**	940	0	35	25
Others	950	0	25	25	**Others**	940	0	35	25

Table D.1.1: State transition matrices of the set of Hidden Markov Models for the different areas for February-March-2020 (pre-pandemic). The values shown correspond to each transition probability ($a_{h,e,l}(i,j)$ multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

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	Children-Area 2					Children-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	275	650	50	25	**Residence**	475	450	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**

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Home	900	50	25	25	**Residence**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	250	400	250	100	**Home**	225	375	300	100
Work / Study	225	625	75	75	**Work / Study**	225	625	75	75
Leisure	300	300	350	50	**Leisure**	275	275	400	50
Others	300	300	250	150	**Others**	275	275	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	725	100	100	75	**Home**	625	100	200	75
Work / Study	725	150	50	75	**Work / Study**	725	150	50	75
Leisure	825	0	100	75	**Leisure**	725	0	200	75
Others	850	0	75	75	**Others**	750	0	175	75

Young people-Area 2					**Young people-Area 11**				
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	275	650	50	25	**Home**	475	450	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	250	400	250	100	**Home**	225	375	300	100
Work / Study	225	625	75	75	**Work / Study**	225	625	75	75
Leisure	300	300	350	50	**Leisure**	275	275	400	50
Others	300	300	250	150	**Others**	275	275	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	725	100	100	75	**Home**	625	100	200	75
Work / Study	725	150	50	75	**Work / Study**	725	150	50	75
Leisure	825	0	100	75	**Leisure**	725	0	200	75
Others	850	0	75	75	**Others**	750	0	175	75

Adults-Area 2					**Adults-Area 11**				
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	750	25	25	**Home**	400	550	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25

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Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	250	450	200	100	**Home**	225	425	250	100
Work / Study	225	675	25	75	**Work / Study**	225	675	25	75
Leisure	300	575	100	25	**Leisure**	275	550	150	25
Others	300	575	100	25	**Others**	275	550	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	700	150	50	100	**Home**	625	150	125	100
Work / Study	700	150	50	100	**Work / Study**	700	150	50	100
Leisure	825	50	50	75	**Leisure**	750	50	125	75
Others	850	0	50	100	**Others**	775	0	125	100

	Older adults-Area 2					**Older Adults-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	750	25	25	**Home**	400	550	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	250	450	200	100	**Home**	225	425	250	100
Work / Study	225	675	25	75	**Work / Study**	225	675	25	75
Leisure	300	575	100	25	**Leisure**	275	550	150	25
Others	300	575	100	25	**Others**	275	550	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	700	150	50	100	**Home**	625	150	125	100
Work / Study	700	150	50	100	**Work / Study**	700	150	50	100
Leisure	825	50	50	75	**Leisure**	750	50	125	75
Others	850	0	50	100	**Others**	775	0	125	100

JUNE 2020

	Elderly people-Area 2					Elderly people-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	800	0	75	125	**Home**	850	0	25	125
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	800	0	75	125	**Leisure**	850	0	25	125
Others	800	0	75	125	**Others**	850	0	25	125
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	925	0	50	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	75	75	**Leisure**	825	0	100	75
Others	850	0	75	75	**Others**	825	0	100	75
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	0	75	25	**Home**	850	0	125	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	900	0	100	0	**Leisure**	850	0	150	0
Others	850	0	0	150	**Others**	800	0	50	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	990	0	5	5	**Home**	980	0	15	5
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	990	0	5	5	**Leisure**	980	0	15	5
Others	990	0	5	5	**Others**	980	0	15	5

Table D.1.2: State transition matrices of the set of Hidden Markov Models for the different areas as of June-2020. The values shown correspond to each transition probability ($a_{h,e,l}(i,j)$ multiplied by 1000) based on age ranges, time slots and changes of location/activity considered.

AUGUST 2020

	Children-Area 2					Children-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	225	700	50	25	**Home**	425	500	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95

sinc(*i*) Research Institute for Signals, Systems and Computational Intelligence (sinc.unl.edu.ar)
Carlos M. Pais, M. Godano, E. Juarez, A. Del Prado, J. Biurrun & H. L. Rufiner; "City-scale model for COVID-19 epidemiology with mobility and social activities represented by a set of hidden Markov models"
Computers in Biology and Medicine, Vol. 160, 2023.

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Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	225	450	250	75	**Home**	200	425	300	75
Work / Study	150	700	75	75	**Work / Study**	150	700	75	75
Leisure	300	300	350	50	**Leisure**	275	275	400	50
Others	300	300	250	150	**Others**	275	275	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	625	100	200	75	**Home**	525	100	300	75
Work / Study	575	150	125	150	**Work / Study**	575	150	125	150
Leisure	725	0	200	75	**Leisure**	625	0	300	75
Others	725	0	125	150	**Others**	625	0	225	150

	Young people-Area 2					**Young people-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	225	700	50	25	**Home**	425	500	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	225	450	250	75	**Home**	200	425	300	75
Work / Study	150	700	75	75	**Work / Study**	150	700	75	75
Leisure	300	300	350	50	**Leisure**	275	275	400	50
Others	300	300	250	150	**Others**	275	275	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	625	100	200	75	**Home**	525	100	300	75
Work / Study	575	150	125	150	**Work / Study**	575	150	125	150
Leisure	725	0	200	75	**Leisure**	625	0	300	75
Others	725	0	125	150	**Others**	625	0	225	150

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		Adults-Area 2					Adults-Area 11		
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	800	25	25	**Home**	350	600	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	500	200	100	**Home**	175	475	250	100
Work / Study	175	725	25	75	**Work / Study**	175	725	25	75
Leisure	275	600	100	25	**Leisure**	250	575	150	25
Others	275	600	100	25	**Others**	250	575	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	150	150	100	**Home**	525	150	225	100
Work / Study	600	150	150	100	**Work / Study**	600	150	100	150
Leisure	700	50	150	100	**Leisure**	625	50	225	100
Others	700	0	150	150	**Others**	625	0	225	150

		Older adults-Area 2					Older Adults-Area 11		
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	800	25	25	**Home**	350	600	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work /**	**Leisure**	**Others**

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							Study		
Home	200	500	200	100	**Home**	175	475	250	100
Work / Study	175	725	25	75	**Work / Study**	175	725	25	75
Leisure	275	600	100	25	**Leisure**	250	575	150	25
Others	275	600	100	25	**Others**	250	575	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	150	150	100	**Home**	525	150	225	100
Work / Study	600	150	150	100	**Work / Study**	600	150	100	150
Leisure	700	50	150	100	**Leisure**	625	50	225	100
Others	700	0	150	150	**Others**	625	0	225	150

	Elderly people-Area 2					**Elderly people-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	750	0	100	150	**Home**	800	0	50	150
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	750	0	100	150	**Leisure**	800	0	50	150
Others	800	0	75	125	**Others**	800	0	50	150
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	925	0	50	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	75	75	**Leisure**	825	0	100	75
Others	850	0	75	75	**Others**	825	0	100	75
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	875	0	100	25	**Home**	825	0	150	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	150	0	**Leisure**	800	0	200	0
Others	800	0	0	200	**Others**	750	0	50	200
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	975	0	10	15	**Home**	965	0	20	15
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	975	0	10	15	**Leisure**	965	0	20	15
Others	975	0	10	15	**Others**	965	0	20	15

Table D.1.3: State transition matrices of the set of Hidden Markov Models for the different sections as of August-2020. The values shown correspond to each transition probability ($a_{h,e,l}(i,j)$ multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

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	Children-Area 2					Children-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	725	50	25	**Home**	400	525	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	475	250	75	**Home**	175	450	300	75
Work / Study	150	725	75	50	**Work / Study**	150	725	75	50
Leisure	275	325	350	50	**Leisure**	250	300	400	50
Others	275	325	250	150	**Others**	250	300	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	100	225	75	**Home**	500	100	325	75
Work / Study	425	150	175	250	**Work / Study**	425	150	175	250
Leisure	675	0	250	75	**Leisure**	575	0	350	75
Others	600	0	175	225	**Others**	500	0	275	225

	Young people-Area 2					Young people-Area 11			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	725	50	25	**Home**	400	525	50	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95

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Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	200	475	250	75	**Home**	175	450	300	75
Work / Study	150	725	75	50	**Work / Study**	150	725	75	50
Leisure	275	325	350	50	**Leisure**	250	300	400	50
Others	275	325	250	150	**Others**	250	300	300	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	100	225	75	**Home**	500	100	325	75
Work / Study	425	150	175	250	**Work / Study**	425	150	175	250
Leisure	675	0	250	75	**Leisure**	575	0	350	75
Others	600	0	175	225	**Others**	500	0	275	225

Adults-Area 2					**Adults-Area 11**				
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	125	825	25	25	**Home**	325	625	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	525	200	100	**Home**	150	500	250	100
Work / Study	150	750	25	75	**Work / Study**	150	750	25	75
Leisure	150	750	25	75	**Leisure**	225	600	150	25
Others	150	750	25	75	**Others**	225	600	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	150	150	100	**Home**	525	150	225	100
Work / Study	475	150	200	175	**Work / Study**	475	150	200	175
Leisure	650	50	200	100	**Leisure**	575	50	275	100
Others	650	0	200	150	**Others**	575	0	275	150

Older Adults-Area 2					**Older Adults-Area 11**				
Time slot 0	**Home**	**Work /**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work /**	**Leisure**	**Others**

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		Study					**Study**		
Home	125	825	25	25	**Home**	325	625	25	25
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	525	200	100	**Home**	150	500	250	100
Work / Study	150	750	25	75	**Work / Study**	150	750	25	75
Leisure	150	750	25	75	**Leisure**	225	600	150	25
Others	150	750	25	75	**Others**	225	600	150	25
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	600	150	150	100	**Home**	525	150	225	100
Work / Study	475	150	200	175	**Work / Study**	475	150	200	175
Leisure	650	50	200	100	**Leisure**	575	50	275	100
Others	650	0	200	150	**Others**	575	0	275	150

	Elderly people-Area 2					**Elderly people-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	725	0	100	175	**Home**	775	0	50	175
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	725	0	100	175	**Leisure**	775	0	50	175
Others	725	0	100	175	**Others**	775	0	50	175
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	925	0	50	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	75	75	**Leisure**	825	0	100	75
Others	850	0	75	75	**Others**	825	0	100	75
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	850	0	125	25	**Home**	800	0	175	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0

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Leisure	800	0	200	0	**Leisure**	750	0	250	0
Others	800	0	0	200	**Others**	750	0	50	200
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	965	0	15	20	**Home**	955	0	25	20
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	965	0	15	20	**Leisure**	955	0	25	20
Others	965	0	15	20	**Others**	955	0	25	20

Table D.1.4: State transition matrices of the set of Hidden Markov Models for the different sections as of October-2020. The values shown correspond to each transition probability ($a_{h,e,l}(i,j)$ multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

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	Children-Area 2					**Children-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	725	75	25	**Home**	375	525	75	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	500	300	50	**Home**	125	475	350	50
Work / Study	100	725	125	50	**Work / Study**	100	725	125	50
Leisure	200	325	425	50	**Leisure**	175	300	475	50
Others	200	325	325	150	**Others**	175	300	375	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	550	100	250	100	**Home**	450	100	350	100
Work / Study	350	150	225	275	**Work / Study**	350	150	225	275
Leisure	600	0	300	100	**Leisure**	500	0	400	100
Others	550	0	225	225	**Others**	450	0	325	225

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Young people-Area 2					Young people-Area 11				
Time slot 0	Home	Work / Study	Leisure	Others	**Time slot 0**	Home	Work / Study	Leisure	Others
Home	175	725	75	25	**Home**	375	525	75	25
Work / Study	25	900	50	25	**Work / Study**	25	900	50	25
Leisure	25	900	50	25	**Leisure**	225	700	50	25
Others	25	900	50	25	**Others**	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	550	300	100	50	**Work / Study**	550	300	100	50
Leisure	800	10	95	95	**Leisure**	750	60	95	95
Others	800	10	95	95	**Others**	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	500	300	50	**Home**	125	475	350	50
Work / Study	100	725	125	50	**Work / Study**	100	725	125	50
Leisure	200	325	425	50	**Leisure**	175	300	475	50
Others	200	325	325	150	**Others**	175	300	375	150
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	550	100	250	100	**Home**	450	100	350	100
Work / Study	350	150	225	275	**Work / Study**	350	150	225	275
Leisure	600	0	300	100	**Leisure**	500	0	400	100
Others	550	0	225	225	**Others**	450	0	325	225

Adults-Area 2					Adults-Area 11				
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	75	825	50	50	**Home**	275	625	50	50
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	525	225	100	**Home**	125	500	275	100

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Work / Study	150	750	50	50	**Work / Study**	150	750	50	50
Leisure	200	625	125	50	**Leisure**	175	600	175	50
Others	200	625	125	50	**Others**	175	600	175	50
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	525	150	225	100	**Home**	450	150	300	100
Work / Study	225	250	225	300	**Work / Study**	225	250	225	300
Leisure	575	100	225	100	**Leisure**	500	100	300	100
Others	525	0	225	250	**Others**	450	0	300	250

	Older adults-Area 2					**Older Adults-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	75	825	50	50	**Home**	275	625	50	50
Work / Study	25	925	25	25	**Work / Study**	25	925	25	25
Leisure	25	925	25	25	**Leisure**	225	725	25	25
Others	25	925	25	25	**Others**	225	725	25	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25	**Home**	850	100	25	25
Work / Study	450	400	100	50	**Work / Study**	450	400	100	50
Leisure	700	120	90	90	**Leisure**	650	170	90	90
Others	700	120	90	90	**Others**	650	170	90	90
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	525	225	100	**Home**	125	500	275	100
Work / Study	150	750	50	50	**Work / Study**	150	750	50	50
Leisure	200	625	125	50	**Leisure**	175	600	175	50
Others	200	625	125	50	**Others**	175	600	175	50
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	525	150	225	100	**Home**	450	150	300	100
Work / Study	225	250	225	300	**Work / Study**	225	250	225	300
Leisure	575	100	225	100	**Leisure**	500	100	300	100
Others	525	0	225	250	**Others**	450	0	300	250

	Elderly people-Area 2					**Elderly people-Area 11**			
Time slot 0	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 0**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	700	0	125	175	**Home**	750	0	75	175
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0

				DECEMBER 2020					
Leisure	700	0	125	175	**Leisure**	750	0	75	175
Others	700	0	125	175	**Others**	750	0	75	175
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 1**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	950	0	25	25	**Home**	925	0	50	25
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	850	0	75	75	**Leisure**	825	0	100	75
Others	850	0	75	75	**Others**	825	0	100	75
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	800	0	150	50	**Home**	750	0	200	50
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	675	0	300	25	**Leisure**	625	0	350	25
Others	675	0	25	300	**Others**	625	0	75	300
Time slot 3	**Home**	**Work / Study**	**Leisure**	**Others**	**Time slot 3**	**Home**	**Work / Study**	**Leisure**	**Others**
Home	960	0	20	20	**Home**	950	0	30	20
Work / Study	1000	0	0	0	**Work / Study**	1000	0	0	0
Leisure	960	0	20	20	**Leisure**	950	0	30	20
Others	960	0	20	20	**Others**	950	0	30	20

Table D.1.5: State transition matrices of the set of Hidden Markov Models for the different areas as of December-2020. The values shown correspond to each transition probability ($a_{h,e,l}(i,j)$ multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

2 Output emission matrices for the states "Leisure" and "Others"

Given that the set of Hidden Markov Models used by AbCSim has two visible states (there is only one possible activity for that state) and two hidden states that can emit different outputs, the emission probabilities $b_{h,e,l}(k,i)$ of the hidden states corresponding to the states "Leisure" and "Others" are shown below.

State	Activity	Children	Young people	Adults	Older adults	Elderly people
Leisure	airport	10	10	10	10	10
Leisure	night_club	0	25	10	0	0
Leisure	art_gallery	10	10	10	10	10
Leisure	Bank	0	0	50	100	100
Leisure	Bar	0	50	100	100	100
Leisure	beauty_salon	50	50	50	50	50
Leisure	bus_station	100	100	50	10	10

Leisure	Casino	0	0	50	80	80
Leisure	church	100	35	50	100	100
Leisure	dentist	50	50	10	50	50
Leisure	doctor	60	60	10	100	100
Leisure	Gym	100	100	100	10	10
Leisure	hair_care	100	60	50	50	50
Leisure	hospital	50	50	50	100	100
Leisure	movie_theater	100	100	100	10	10
Leisure	museum	50	50	50	50	50
Leisure	physiotherapist	50	50	50	100	100
Leisure	restaurant	50	50	50	10	10
Leisure	stadium	150	100	100	50	50
Leisure	Spa	0	2	10	10	10
Others	ATMs	0	10	50	50	50
Others	bakery	25	25	10	10	10
Others	bicycle_store	50	40	25	25	0
Others	book_store	25	25	25	25	25
Others	Café	1	1	25	25	25
Others	car_dealer	0	2	10	10	10
Others	car_repair	0	2	25	25	25
Others	car_wash	0	2	10	10	10
Others	cemetery	0	2	10	10	50
Others	clothing_store	50	38	50	50	50
Others	convenience_store	25	25	10	10	10
Others	drugstore	50	50	50	50	50
Others	electronics_store	100	100	50	50	50
Others	florist	0	0	10	10	50
Others	furniture_store	0	1	10	10	10
Others	gas_station	1	1	25	25	25
Others	hardware_store	100	100	25	25	25
Others	home_goods_store	25	24	25	25	25
Others	insurance_agency	0	0	10	10	10
Others	jewelry_store	0	2	10	10	10
Others	laundry	1	1	10	10	10
Others	lawyer	0	0	10	10	10
Others	library	25	25	10	10	10
Others	liquor_store	0	20	20	20	20

Others	locksmith	0	0	10	10	10
Others	meal_delivery	25	25	25	25	25
Others	meal_takeaway	25	25	25	25	25
Others	movie_rental	50	50	10	10	10
Others	parking	0	0	25	25	20
Others	pet_store	100	80	25	25	25
Others	pharmacy	25	25	50	50	50
Others	post_office	25	25	25	25	25
Others	real_estate_agency	0	0	10	10	10
Others	shoe_store	25	25	25	25	25
Others	shopping_mall	100	100	100	100	50
Others	storage	25	25	25	25	25
Others	supermarket	50	50	100	100	100
Others	travel_agency	25	25	10	10	10
Others	veterinary_care	47	47	10	10	10

Table D.2: Output emission matrices $B_{h,e,l}$ for the states "Leisure" and "Others" of the set of Hidden Markov Models ($b_{h,e,l}(k,i)$ multiplied by 1000) used for the simulations.

3. Google Mobility® versus agents Ha's mobility.

In previous sections HMM probabilities in A and B matrices for all age ranges, time slots and neighborhoods, for the different phases of PMSI were shown. These were obtained by expert knowledge and field surveys, and then corroborated with Google Mobility® records.

As an illustration of this procedure, Figure B.1 shows the comparison between Google Mobility® data and the corresponding Ha's relative mobility central tendency estimated from model simulations during a period in which there were no PMSI changes. Both mobilities curves were relative to February 2020, when there were no Covid-19 in Argentina. This methodology was a meant to corroborate that the mobilities derived from A and B matrices were in an appropriate scale by contrasting them with real data. This "calibration" stage was carried out each 15 days after a PMSI change were announced by the local government.

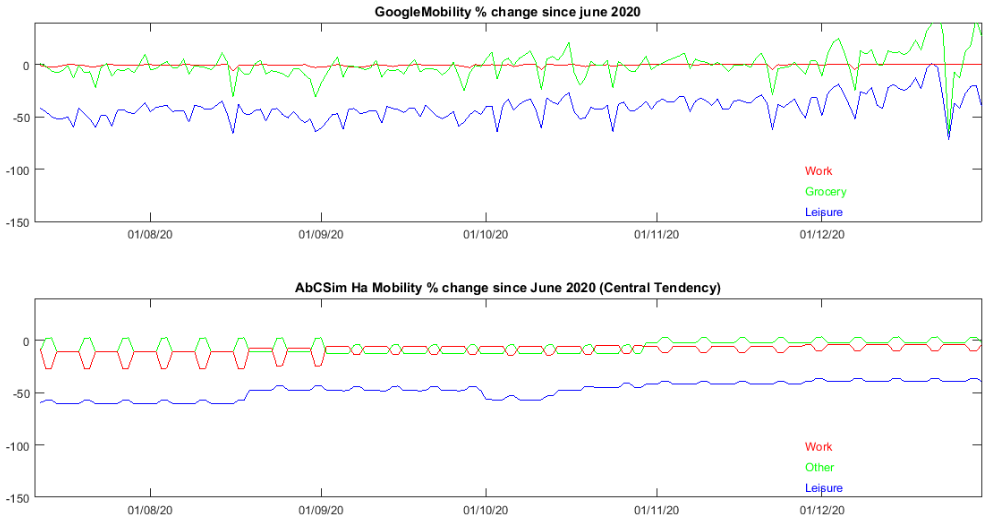

Figure D.1: Relative mobility curves from June to December 2020 for Paraná city (compared to the pre-pandemic condition of February 2020). In the upper panel Google Mobility® data is shown: In red the relative mobility for people at work is presented, in blue for people in leisure activities and in green for people at groceries. In the lower panel simulated Ha's relative mobility central tendency is shown: In red the relative mobility for Ha agents at work is presented, in blue for Ha in leisure activities and in green Ha at other activities.

4 Variation of parameters related to the Interpersonal Contact Submodel

Since some of the values of the model parameters depend on the change of PMSI phases the following Table B.4 shows how they change according to the time of the year in which the simulation is run and the corresponding provisions (2020).

Dates	**12/ Jun**	**01/ Jul**	**20 / Jul**	**03/ Aug**	**17/ Aug**	**31/ Aug**	**11/ Sep**	**14/ Sep**	**21/ Sep**	**01/ Oct**	**29/ Oct**	**06/ Nov**	**06/ Dec**	**09/ Dec**	**14/ Dec**	**24/ Dec**	**31/ Dec**
Mask Protection (%)	30	30	30	30	30	30	30	25	25	25	25	25	25	25	20	20	20
Observance of social distancing (%)	80	80	60	60	30	25	20	20	20	20	20	20	20	20	10	10	10
Capacity in "Others" (m^2)	4.00	4.00	4.00	3.00	3.00	1.50	1.50	1.50	1.50	1.60	1.60	1.60	1.60	1.60	1.50	1.00	1.00
Capacity in "Leisure" (m^2)	4.00	4.00	4.00	4.00	4.00	1.50	1.50	1.00	1.10	1.75	1.80	1.80	2.10	2.10	2.10	1.50	1.50

Table B.4: Variation of parameters of Interpersonal Contact Submodel according to date and changes in the isolation or distancing phases (2020).

4 Preliminary Sensitivity Analysis

With the purpose to analyze which are the principal parameters that lead to great variations in the output of the AbCSim, a preliminary sensitivity analysis “One at a time” was conducted for the period between July and November 2021. In Figure D.4, a sensitivity analysis graph for the main model outputs is presented (number of ICU beds, asymptomatic and symptomatic patients). With the aim of simplicity, only the three most important parameters are presented here (Contagion probability, places capacity and contagion distances).

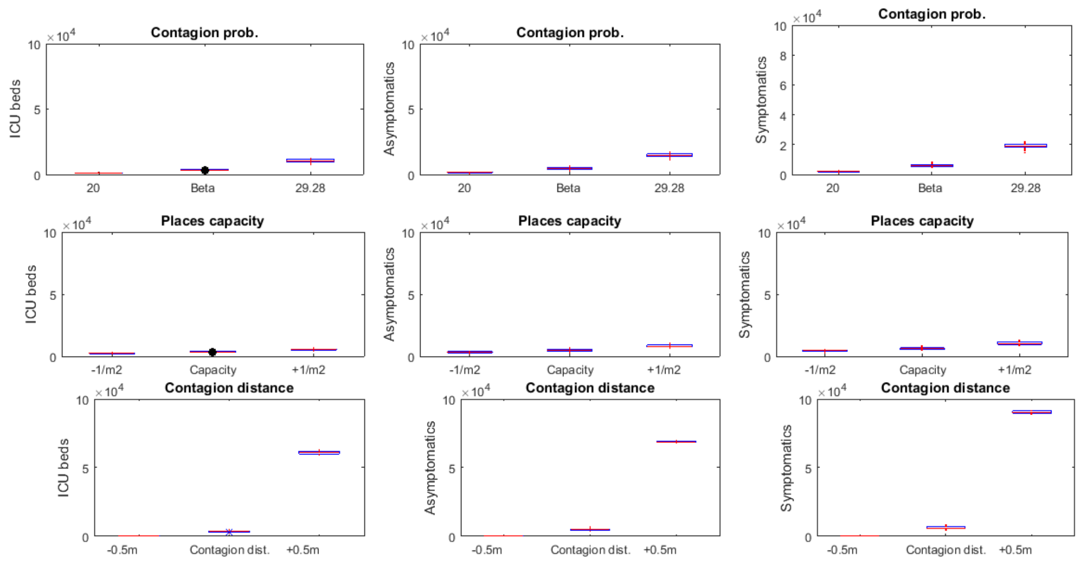

Figure D.2: “One at a time” sensitivity analysis graphs in “Box Plot” format. Upper row: Contagion Probability (β). Middle row: Places capacity, i.e. the number of people per m^2 allowed to occupy facilities or shops. Bottom row: Contagion distance, which is the radius in which any person is susceptible to be infected by other infected person, if they stay that close for more than 20 minutes. Left column: Cumulative (July to November 2020) number of ICU beds obtained from de PMUC provincial state program is presented in a stem point in black. Middle and right columns: Cumulative number of asymptomatic and symptomatic infected Ha respectively.