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ABSTRACT

In this paper, an agent-based model that predicts a daily evolution of the number of people hospitalized in intensive care due to COVID-19 is presented, including results for 2020. In addition, the number of deaths, reported cases, asymptomatic individuals and other epidemiological variables of interest, discriminated by age range, are considered. The most relevant characteristics of the climate in Paraná city (Entre Ríos, Argentina), its social dynamics and public transportation are considered as inputs, taking also into account the different phases of isolation and social distancing. By means of a set of Hidden Markov Models, the system reproduces virus transmission associated with people's mobility and activities in the city. 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 a proportion of asymptomatic infected people. By adjusting the model to match the data on hospitalizations in intensive care units and deaths due to COVID-19 in the city under study, the system can be operated to analyze the impact of isolation and social distancing measures on the population dynamics. In addition, it allows simulating combinations of characteristics leading to a potential collapse in the health system due to lack of infrastructure, as well as predicting the impact of social events or the increase in people's mobility.

Keywords: Agent based model, Hidden Markov model, COVID-19, epidemiology, georeferencing, virus transmission, virus spread.

INTRODUCTION

In March 2020, the novel coronavirus SARS-CoV-2 that produced the COVID-19 outbreak infected more than 270,000 people all over the world and killed more than 11,300 [1]. The epidemiological analysis of the different outbreaks of this disease, which have been recorded worldwide, has helped develop different models, mainly mathematical, to track and anticipate the spread of epidemics [2][3][4][5]. It is within this context that the present work arises, with the aim to provide an alternative that allows including more factors of reality and to predict the impact of different social and health policies.

According to current epidemiological reports, this pandemic has characteristics rarely seen for other infectious diseases [6]. Some of the particularities of COVID-19 are: its high basic reproduction number (R_0) of up to 2.79 [7]; an asymptomatic infectious period of up to 14 days, in which there is a group of individuals with no symptom onsets and the disease can be detected only through a serological test; and a great variability in time and clinical repercussions [8]. It has been proven that the dynamics of this epidemic varies mainly according to the climate [9], social and health local habits [10] [11], comorbidities [12] and age range [13], among other variables. The multiplicity of factors influencing this pandemic requires a different approach, as it is necessary to focus on the formulation of more complex and realistic computational models, which include specific characteristics for each area under study, rather than on conventional models, mainly mathematical ones. Thus, this paper proposes a novel model that incorporates local aspects, such as social, cultural, geographical and climatological variables, linked to the epidemic under study and to its transmission modes.

Much of the reported literature on modeling and simulation of epidemics, in particular COVID-19, proposes global models based on differential equations of SEIR (Susceptible, Exposed, Infected, Recovered) type or similar ones, with their different variants adapted to this disease [14][15]. However, the epidemic modeling community has been using local or fine-grained models [16], including agent-based models (ABM) [10][13][17][18], such as the one used in this work. These models allow 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 [10][11][19]. On the other hand, they require greater computational power and access to a large amount of local data in order to be adapted to particular situations.

ABM 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 certain rules, forming a social architecture. The social aspect is given by the heterogeneity, autonomy, interdependence, and social embedding that characterize the computational agents [20]. To our knowledge, few models with this characteristics have been applied to COVID-19 [10][11][21][22][23]. Furthermore, most of these models have been designed for specific situations in some region or country and it is difficult to extrapolate them to new particular situations, as lot of scientific and technical knowledge is required for this purpose.

This paper presents a novel model called *Agent-based model for COVID-19 Simulation* (AbCSim) that allows the modeling of the group of people with COVID-

19, either symptomatic or asymptomatic cases, together with those considered to be susceptible or recovered population [24]. This model takes into account the complexity of the dynamics of the pathology and the interpersonal relationships of the populations, 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) [25][26][27], which reflect the main aspects of the mobility and social activities of the agents within the modelled geographical region. AbCSim runs on the computational simulation platform Repast [28] and is open source (via GitHub)[1]. The proposed model allows the simulation of the entire population, on an individual, one-by-one basis, at city scale (or larger). It was tailored for Paraná city, (Entre Ríos, Argentina)[2] and tested under different situations to predict the local evolution of the epidemic.

METHODS

Proposed model: Agent-based COVID-19 Simulator (AbCSim)

1. Description and general scheme of the model

Repast [29] is a platform with a set of open source modeling and simulation tools based on agents that runs on different operating systems. For each experiment or new scenario tested, a computer *cluster* is required to run several instances of the model simultaneously, which generates results based on central trends, given the stochastic nature of the phenomenon under study. This platform allows the implementation of agents' characteristics, behaviors and interactions with each other and with their environments. The general scheme of the model is presented in Figure 1, and it shows different levels of detail. The first general level represents the complete model (black

[1] https://github.com/Repastero/GeoCOVID-19
[2] https://www.parana.gob.ar/la-ciudad/caracteristicas.php

block), with its initial conditions, inputs and outputs. The second level shows the main blocks of the system (blue blocks): a block for the simulation of 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 [30]. The next level (green blocks) shows the submodels of *Epidemiological characterization* and *Infectivity* for each agent and their corresponding parameters. It also presents *Interpersonal contact*, *Location* and *Mobility/Activity submodels*, and the specific parameters for this submodel. Finally, the third level also shows the *Transport* and *Infectious trail* submodels (magenta blocks). Each submodel will be described in further detail in the following sections.

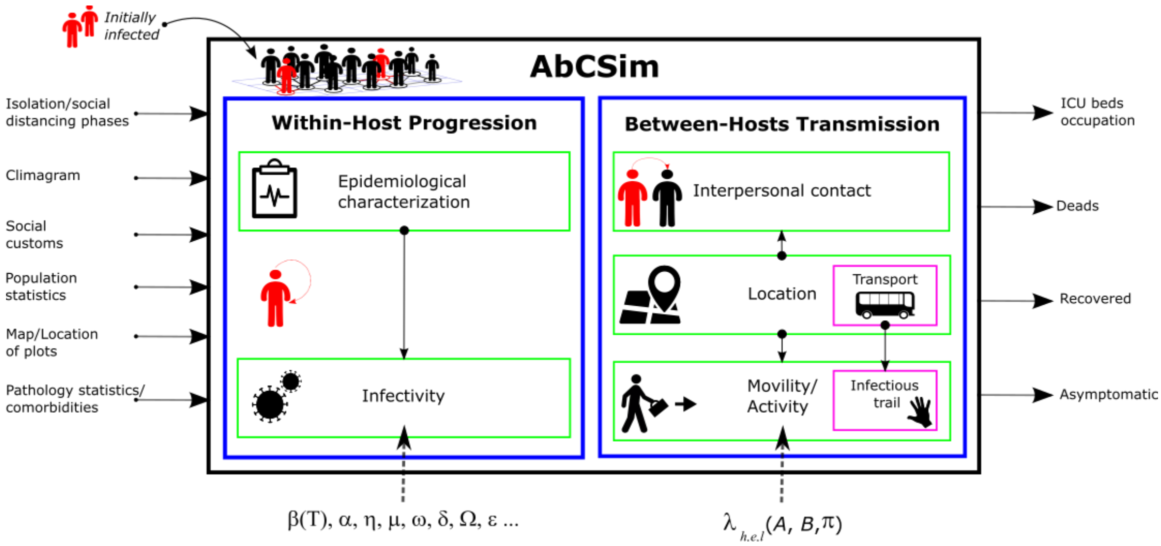


Figure 1: AbCSim block diagram: General model (black block) with inputs, outputs (horizontal solid line arrows) and initial conditions (curved arrows); main functional blocks (blue left and right-side blocks) and the corresponding submodels for each block (green and magenta blocks). Vertical solid line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

2. Agents, attributes and general behaviors.

Since it is an ABM, the core of the model is constituted by agents named *human* (H_a). Each H_a has the ability to acquire and transmit SARS-CoV-2 virus; to change the symptoms and health state, according to the infection spread, and to change behaviors accordingly (*Infectivity* submodel, Section 3.1). Besides, each H_a has specific characteristics and attributes corresponding to specific risk factors and comorbidities (*Epidemiological characterization* submodel, Section 3.2).

The most important relationships between human agents, regarding COVID-19 epidemiology, are represented in the *Interpersonal Contact* submodel (Section 4.1). This submodel also presents human agents' relationships with each other, with the plots of land, and with the environment. These relationships are affected by average distance in the different places they attend, how long the stay and the observance of mask use and social distancing rules (Sections 4.1 and 4.2).

For *Location* submodel, a specific geographic information system (GIS) module of Repast platform is used, which will be further described in Section 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 other specific location for people gathering. This can be seen in *Transportation* submodel (Section 4.2.1). The level of detail and quality of the specific geographical information in this system are vital to accurately represent the mobility and activities of each H_a in this simulated society.

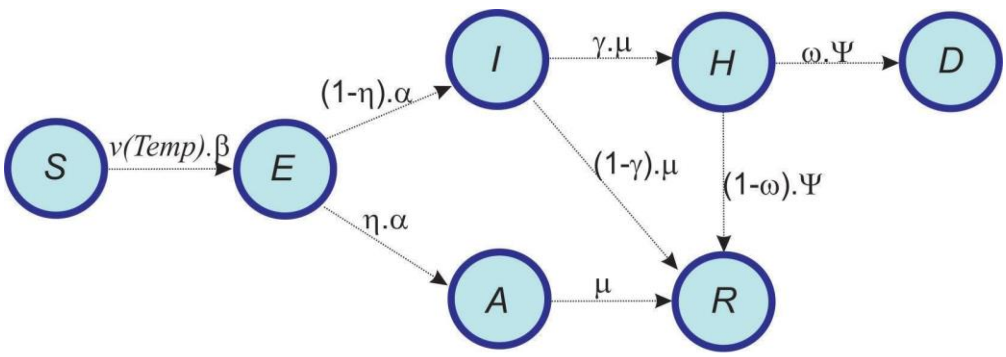
On the other hand, each H_a has a particular behavior according to its age range, habits and neighborhood where it lives, randomly assigned at the beginning of each simulation, following the population statistics for the city. Considering this, each H_a moves individually according to probabilities ($A \epsilon \lambda_{h,e,l}(A, B, \pi)$) associated with state change matrices (activities/locations) of a set $\lambda_{h,e,l}$ of HMM that represent the *Mobility/Activity* submodel. Each HMM corresponds to a place (l) (neighborhood/city/area) where H_a lives, to its age range (e) , and to the time slot (h) it is in at the time of the simulation. The description of this submodel will be resumed in Section 4.3. Finally, the permanence of active virus in different locations/environments is represented by the *Infectious trail* submodel described in Section 4.3.1.

3. Block of Virus Spread in the Host.

3.1. Infectivity Submodel.

AbCSim infectivity submodel is based on a mathematical model proposed by Arenas et al. [31], which was translated to Repast as the virus spread process in human agents.

Each H_a has a state attribute according to one of these seven epidemiological compartments in which the metapopulation is divided[3]: **S**: susceptible; **E**: latent or exposed; **I**: symptomatic infectious; **A**: asymptomatic infectious; **R**: recovered; **D**: dead and **H**: hospitalized. Figure 2 shows the different components, relationships and parameters of this submodel as a diagram.



[3] Although the concept "compartment" is more commonly used in epidemiological literature, from a formal point of view, this submodel can also be seen as another finite state stochastic automaton.

Figure 2: Spread submodel 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. [31] (see parameters details in the text).

This submodel comprises all the COVID-19 pandemic specific characteristics, such as important epidemiological effects caused by asymptomatic infectious individuals (**A**) or with mild symptoms. The fraction of individuals requiring hospitalization in intensive care (**H**) is also considered and it is assumed that all human agents have the possibility of accessing a respiratory ventilator, since the local healthcare capacity was not exceeded in the city under study.

Taking into account the aforementioned characteristics of human agents, this submodel operates as follows: the susceptible H_a becomes infected with a probability β due to interpersonal contact with another infected H_a either symptomatic (**I)** or asymptomatic (**A**). This probability of infection is modulated by a variable v, dependent on daily mean temperature. If the susceptible individual (**S**) becomes infected, H_a becomes part of people exposed to the virus (**E**). Exposed individuals, $\frac{1}{\alpha}$ days later, become asymptomatic or symptomatic, according to a characteristic probability η , depending on H_a's age range. Once infected, there are two possibilities. The first option is that H_a requires hospitalization (**H**) in intensive care unit (ICU), with a certain probability γ, according to H_a's age range, comorbidities and risk factors. Risk factors or comorbidities are attributes of each H_a, and the increase in the probability of moving to ICU that they represent is shown in Table 2 in the following section (*Epidemiological characterization* submodel). If H_a, after $\frac{1}{\mu}$ days is not transfered to ICU, then it is considered recovered and not re-infected, at least for an average period of 11 months, according to [32]. During the stay in ICU, individuals have a death probability ω [33] after an average period of $\frac{1}{\Psi}$ days [34][35]. After this period,[4] H_a vacates the ICU bed and moves to Recovered compartment.

Human agent population were 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 1.

Age range	Children 5-14 years old	Young people 15-24 years old	Adults 25-39 years old	Older adults 40-64 years old	Elderly people
η Probability of changing to asymptomatic	0.74	0.58	0.42	0.26	0.10
γ Probability of going to ICU	0.00011	0.00031	0.00081	0.0464	0.3051
ω Probability of death in ICU	0.42	0.42	0.42	0.42	0.42
β Probability of transmission	0.26	0.26	0.26	0.26	0.26
$\frac{1}{\alpha}$(days) Incubation period	5.2 ± 1	5.2 ± 1	5.2 ± 1	5.2 ± 1	5.2 ± 1
$\frac{1}{\mu}$(days) Infection period	5 ± 1	5 ± 1	5 ± 1	5 ± 1	5 ± 1
$\frac{1}{\Psi}$(days) ICU stay	4 ± 1	4 ± 1	4 ± 1	4 ± 1	4 ± 1

Table 1: Values of the Spread submodel parameters used. Those for which mean value ± standard deviation is specified have normal probability distribution. Adapted from [31].

[4] 2020, Clarín. 2020. "Coronavirus en Argentina: ¿cuánto tardan los enfermos en recuperarse?"//"Coronavirus in Argentina: how long does it take for patients to recover?" Interview with Rosa Reina, president of the Argentine Society of Intensive Care. https://www.clarin.com/sociedad/coronavirus-argentina-tardan-enfermos-recuperarse-_0_M_gF-DJnj.html.

Infectivity submodel makes behavior of H_a change according to its epidemiological compartment. If H_a is in the Susceptible compartment, then H_a meets the daily activities and movements pre-established as attributes and defined by *Mobility* submodel. However, if H_a is in a *compartment* different from Susceptible or Exposed, then H_a stops moving, since it is assumed that it remains at home to avoid transmiting the disease to other H_a. From that moment on, the household members are in the Exposed compartment.

Finally, in AbCSim the transmission probability from an interpersonal contact is a parameter linked not only to strictly epidemiological aspects, as β is also multiplied or modulated by the variable v, which evolves throughout the year and is inversely proportional to daily mean temperature, according to studies that define COVID-19 as a seasonal disease [36][37][38]. In this way, 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 daily mean temperature is higher in the southern hemisphere.

3.2. Epidemiological Characterization Submodel.

As mentioned in the previous section, each H_a has specific epidemiological values that affect the *Infectivity* submodel parameters shown in Table 1. Among these attributes, we can highlight: the existence of comorbidities or risk factors and the existence of symptomatic infected household members.

Comorbidities increase the probability γ of going from infected to inpatient in ICU according to the percentage value presented in Table 2 [33].

Pathology	Increase in probability of ICU admission
Respiratory	0.1230
Diabetes	0.3100
Hypertension	0.2889
Obesity	0.5863

Table 2: Increase in probability γ of moving from infected to hospitalized in ICU, according to the particular comorbidity H_a has.

Finally, there are two attributes linked to the H_a's behavior which 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 *Interpersonal Contact* submodel (Section 4.1).

4. Host Spread Block

4.1. Interpersonal Contact Submodel

For each H_a, there is a method that measures whether there is another agent within a 2-m range [39][40][41]. If this proximity lasts for 15 minutes or longer and either agent is infected (symptomatic or asymptomatic), then the epidemiological state attribute of the not infected H_a changes to exposed **(E)**, with probability $v(Temp) * \beta$.

For each Ha, the model considers the current national definition of "close contact "[5]. This routine causes an automatic state change from susceptible **(S)** to exposed **(E)** for the household members who live with a symptomatic infected, regardless of whether

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

interpersonal contact has been corroborated. In addition, as previously mentioned, each H_a has an attribute that expresses the observance of mask use. This attribute makes β to be affected by another coefficient, named *mask*. This coefficient modulates β when there is a close contact, subtracting a 30% [17][21][42][43] of its value when H_a shows a high level of observance of mask use. When this level of observance is low, then *mask* coefficient is not applied.

Finally, this submodel takes into account an attribute of each H_a that is defined by the level of observance of social distancing. This attribute, *distancing,* has two possible values: *high* or *low*. In the event that H_a has *high* level of observance, before taking any position in the geographical grid that does not correspond to its home, it checks that there is no other agent in a diameter of 1.8 m. If this condition is verified, then H_a takes the place. If not, it waits until the corresponding capacity allows it. On the other hand, if distancing has a *low* value, then, when this H_a moves, it takes the corresponding place, regardless the allowed capacity.

4.2. Location Submodel.

With the aim of achieving an approximate representation of locations where citizens live, work, consume and perform leisure activities, GIS tools included in Repast were used. This information, together with movements verified during the day, configures the *gregarious habits* of each H_a. These habits were determined through 441 individual field surveys, complying 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[6].

[6] 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.

To represent buildings as houses, workplaces, shops, recreational places, etc., city grid maps were used (they were provided by Paraná Municipality Land Registry Office). Tools such as Google Maps and Google Places® were also used[7], 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*, in order to verify the information provided by the resources mentioned. In this way, assisted by tracking tools based on GPS, the GIS map was completed with the field survey. With this information in the system start routine, each H_a is assigned the attributes linked to this submodel, until filling the entire map with the number of human agents corresponding to each plot of land.

Figure 3 shows a map of Paraná city neighborhoods or districts No.° 2 and N. ° 11 with a level of detail showing the main AbCSim places of interest and activities carried out at those places.

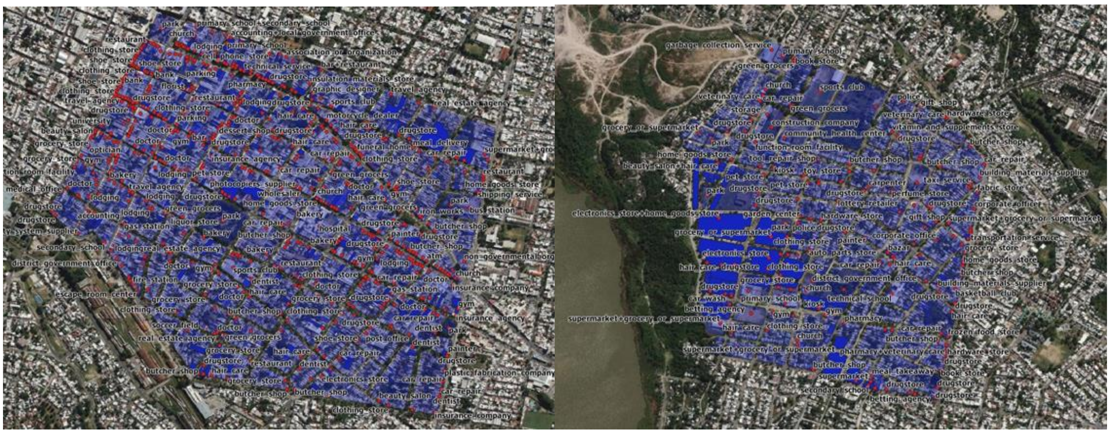


Figure 3: GIS Map of the Areas No. ° 2 (left) and No. 11 (right) in Paraná city, used for Location submodel.

[7] 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

4.2.1. Transportation Submodel.

This block represents the influence that public transportation has in 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 for this study. Human agents can enter this plot once every 20 min (average frequency of local transportation), and remain at an average distance of 2 m, for 20 min. Distancing is not met only for one minute, which would represent the time that takes to go from the entrance door to the seat and from the seat to the exit door. After 20 minutes, each H_a can either move to a new position on the map or stay in the transportation position for another equal period of time (depending on a transition probability defined by *Mobility/Activity* submodel, which will be discussed in the next section).

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

4.3. Mobility/Activity Submodel

This submodel helps simulate the mobility or movements of human agents living in a district or *neighborhood* of the model, considering age range and time slot being simulated. It also establishes the type of activity that each H_a will perform in the location where it is to be at the next period of time considered. Some of these activities are unique to each H_a 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).

To calculate the position of each H_a at each instant, AbCSim generates a series of waypoints in specific geographical locations from a set of HMM [25]. Each of these HMM defines the probabilities of moving from one position to another one, depending on the position occupied by H_a in the previous instant and on the activities defined for the H_a's particular attributes.

It is considered that the behavior linked to each H_a's mobility is different at different times of the day, so specific HMM are generated for different time slots. The same occurs for age ranges. According to their age range, each H_a has a characteristic type of mobility and activities shared by all the human agents of the same neighborhood or district.

Assuming that virus transmission in streets is practically negligible and that, therefore, it has no impact on the model, it is postulated that, for H_a, mobility on foot from one plot to another is immediate. As described in the previous section, only dynamics of mobility by public transportation are represented, where appropriate, since this type of mobility is considered as a possible activity for the state *Others*, which will be discussed below.

The set of HMM that comprises *Mobility* submodel is defined as $\lambda_{h,e,l}(A, B, \pi)$. There is a particular $\lambda_{h,e,l}$ HMM for each H_a, based on age range (e), neighborhood (l) and time slot (h) corresponding to simulation time.

As shown in the state graph in Figure 4, all HMM have four states. 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 $a_{h,e,l}(i,j)$, that is, to move from a 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 H_a in the 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 citizens start the day at home.

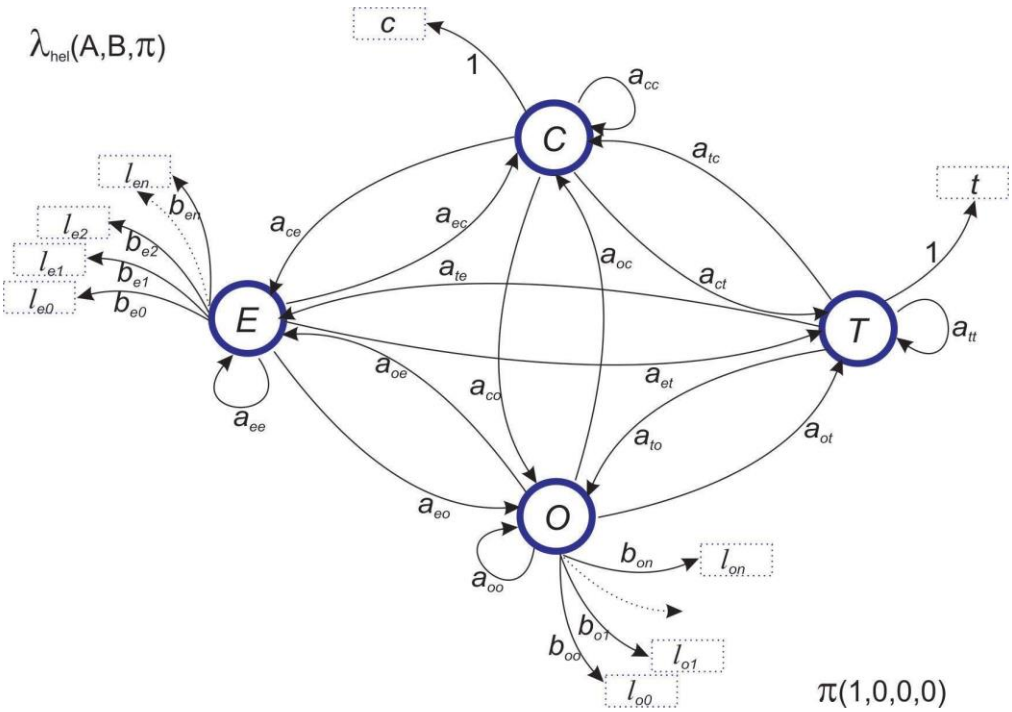


Figure 4: State graph of a Markov submodel. The four states, circled, represent ***C***: House; ***T***: Work; ***E***: Leisure; ***O***: Others. Rectangular blocks show possible outputs for each state, i.e. each waypoint. States ***H*** and ***W*** have only one possible output (defined in the attributes of each H_a), 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 H_a's neighborhood. State ***O*** selects its output randomly.

The possible states have the following specific characteristics:

- **C:** This location represents H_a*'s* home and, therefore, has only one possible outcome. The specific location in the geographical map of the city that means the output for this state is defined as an attribute for each H_a and is part of the *Location* submodel. 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 H_a. This point on the geographical map can be shared by multiple human agents. For some H_a, it coincides with that of their home (for those who do not work or study). The work/study location is fixed for each H_a, 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 human agents according to their age ranges.
- **E:** The location defined as "leisure" represents a place usually visited by people routinely and is shared by several H_a. 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 particular neighborhood.
- **O:** Those defined as "other locations" are less frequent. As examples, ATMs, warehouses, restaurants, supermarkets, pharmacies and public transportation can be mentioned.

Time slots are defined as follows:

- Morning: 8:00 -12: 00, time slot 0;
- Early afternoon: 12:00 - 16: 00, time slot 1;
- Afternoon: 16: 00 - 20: 00, time slot 2;
- Evening: 20: 00 - 24: 00, time slot 3

Age ranges are defined as follows:

- Children: 5-14 years old, age range 0;
- Young people: 15-24 years old, age range1;

- Adults: 25-39 years old, age range 2;
- Older adults: 40-64 years old, age range 3;
- Elderly people: over 65 years old, age range 4

As an example, Table 3 shows matrix values $A_{h,e,l}$ for the HMM of a particular neighborhood l for age range 0 (*Children*) and time slot 0 (*Morning*). So, $a_{0,0,l(i,\,j)}$ has the probabilities that a child (e = 0) of neighborhood l, during the morning (h = 0), moves from state i (row) y to the state j (column). In particular, $a_{0,0,l}(1, 2) = 25$ is the probability value (multiplied by 1000) that a child from the neighborhood l, within the time slot 0 leaves work/study (1) and goes to a leisure location (2). **Appendix A** presents probabilities A and B for all age ranges, time slots and neighborhoods defined in AbCSim, for the first phase of the Preventive and Mandatory Social Isolation (PMSI) ruled by the Argentine National Government.

Time slot 0 (8.00 - 12.00)		Goes: Home	Goes: Work/ Study	Goes: Leisure	Goes: Others
Leaves	Home	50	875	25	50
	Work / Study	25	900	25	50
	Leisure	25	900	25	50
	Others	25	900	25	50

Table 3: Matrix values A for HMM for age range 0, time slot 0 for human agents in a particular neighborhood l in the city (in probabilities, multiplied by 1000, that H_a "leaves" one location and "goes" to another location).

4.3.1. Infectious Trail Submodel

This submodel represents the possibility of H_a to become infected due to the contact with surfaces previously contaminated by another H_a. According to some studies [44] [45], the most common everyday materials to human contact are plastics. There, the virus can last for a time that depends exponentially and inversely on ambient temperature. If an infected H_a remains in a given location longer than 16 minutes, it is possible that it leaves an infectious trail on the objects handled (*fomites*). This can be mathematically modeled [44] 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 system GIS projection, making each cell where an infected H_a remained able to infect another H_a 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 it has no significant impact.

5. Obtaining and adapting AbCSim parameters.

As described in previous sections, the model consists of different blocks and submodels, each of them with its own characteristic parameters that need to be adjusted for its correct functioning.

Due to the heterogeneous nature of AbCSim, each submodel 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.

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

The particularities of each block are described below, while **Appendix A** details the main parameters of the model, in order to provide reproducibility to this work and its results.

5.1. Block of Virus Spread in the Host.

Based on the values proposed by the literature [31], an initial calibration of parameters linked mainly 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 (small village in northern Italy) [46] was used and, in addition, the geographical, climatic, demographic and habits data of its inhabitants[8].

To validate the model, the initial conditions and parameters related to host transmission in the city of Hoyo de Manzanares were applied[9] [47]. In this case, following the methodology presented by other epidemiological models based on

8 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

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

agents [13][48], it was verified that AbCSim outputs agree with data collected on field, and that the model output dispersion, measured in terms of the interquartile range, is acceptable.

Finally, in order to test the model against habits verified for Argentine cities, a simulation was run with actual data obtained from the district of Loncopué, Neuquén province[10] [11]. 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 1.

5.2. Host Spread Block

The values of *mask* and *distancing* in *Interpersonal Contact* submodel were set in agreement with the literature presented in Section 4.1. As the isolation and distancing phases changed, the increase in people's mobility was verified, which was reflected in the information provided by Google Mobility[12]. The change in people’s mobility towards activities of normal pre-pandemic life is reflected in the changes in parameters of matrices *A* and *B* of various HMM presented in **Appendix A**.

RESULTS AND DISCUSSION

This section presents the simulation output results obtained with AbCSim, with data and adjustment of the parameters corresponding to the city under study, from June 12,

[10] https://www.clarin.com/sociedad/coronavirus-argentina-loncopue-pueblo-asado-propago-enfermedad_0_t7IEWiIT6.html
[11] https://www.lanacion.com.ar/sociedad/coronavirus-neuquen-aisla-loncopue-pueblo-donde-se-nid2352684/
[12] https://www.google.com/COVID19/mobility/

2020, when local cases began rising most significantly, through December 30, 2020. Model was fed with city climograph, 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, obtained from Entre Ríos province Critical Units Monitoring Program (Programa de Monitoreo de Unidades Críticas, PMUC), during the period under study, and the estimate obtained by the model. This information is extremely important in order to anticipate a possible local health care system strain. In addition, this data set that can be obtained from reality quite accurately. This figure confirms that weekly reports of ICU beds occupancy with COVID-19 patients are compatible with the model output values.

Figure 6 shows the number of daily COVID-19 cases (symptomatic and asymptomatic) estimated by the model in the period under analysis. In this case, official numbers only consider a sample of the actual total cases, since official reports are highly dependent on testing policies and on cases monitoring, appart from the difficulty in detecting asymptomatic cases. The model estimates that the number of actually infected people is larger than that showed by official reports. This agrees with the bibliography reported for other case studies [49].

Finally, Figure 7 shows accumulated number of deaths from COVID-19 estimated by the model in the period under study. This model output is directly verifiable with data field, and it follows that the number of accumulated deaths matches the amount reported by the UTN FRCU - COVID-19 GIBD Research Group Databases [13] for Paraná city.

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

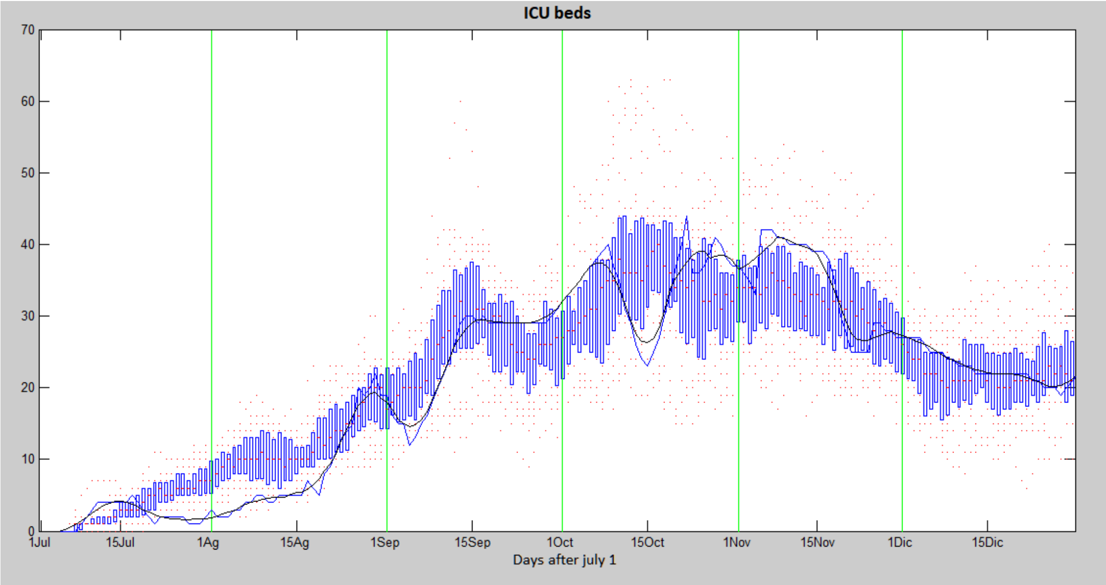


Figure 5: ICU beds occupied by positive COVID-19 patients in the period under study. Black shows ICU beds for Covid-19+ surveyed by the Critical Units Monitoring Program of Entre Ríos province; blue, the dispersion of the corresponding model output; and red, its central tendency.

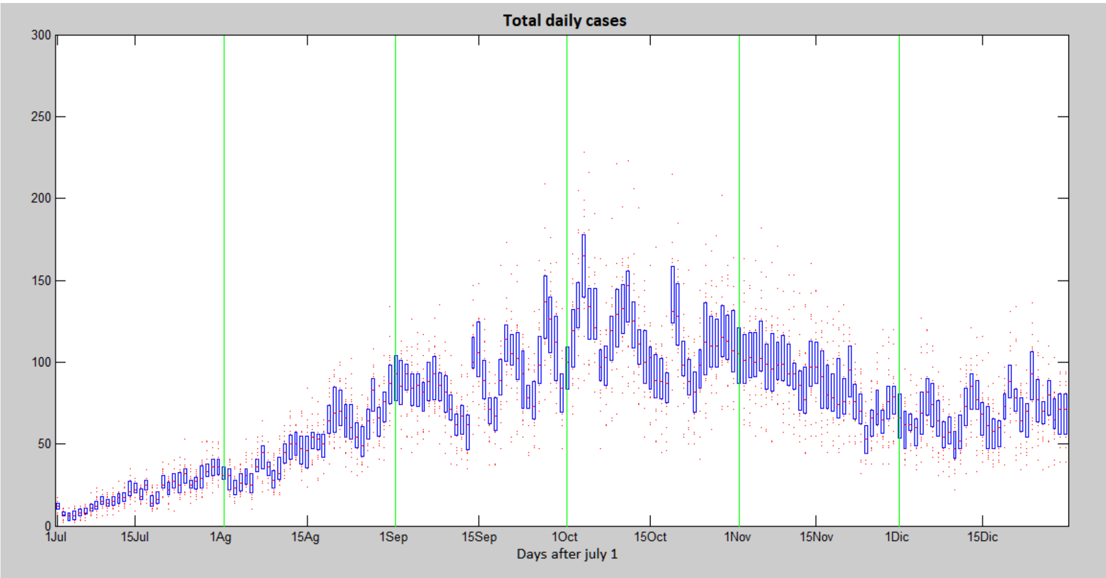


Figure 6: Daily COVID-19 cases (symptomatic + asymptomatic) estimated by the model in the period under study. Blue shows the dispersion of the model output and red, its central tendency.

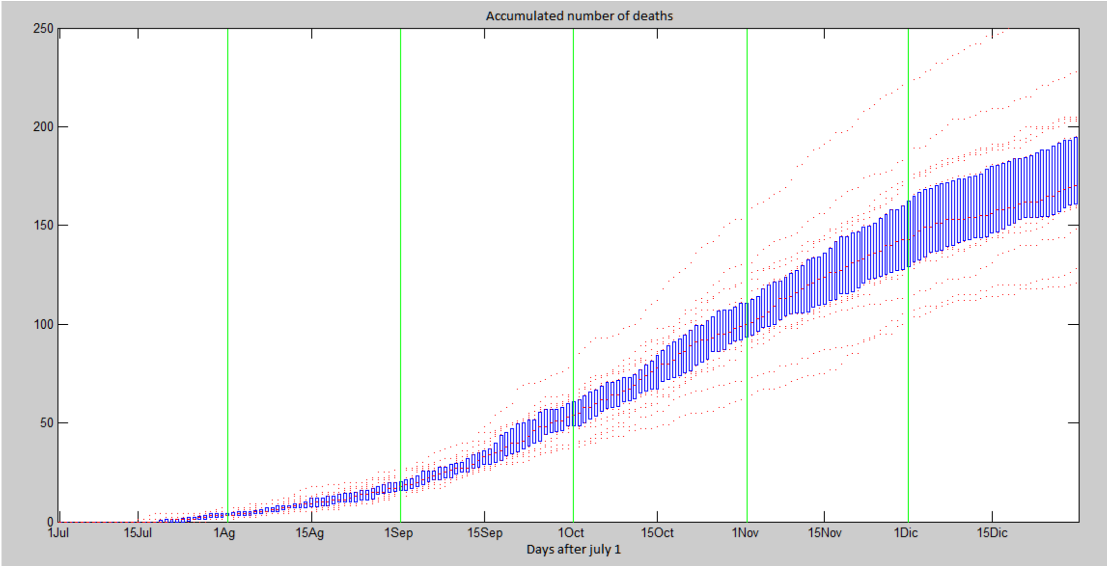


Figure 7: Accumulated number of deaths due to COVID-19 estimated by the model in the period under study. Blue shows the dispersion of the model output and red, its central tendency.

CONCLUSIONS

This work presents an agent-based model called AbCSim, 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 in the second half of 2020.

The results obtained 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 model outputs agree with the number of deceased people reported for the period of time considered. It can be concluded that the model can be used to predict the most likely evolution of the number of cases and number of beds to be occupied in the short term.

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

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Conflict of interest:

The authors have no conflicts of interest to declare.

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Authors' contributions:

Carlos M. PAIS was responsible for conceptualizing the work; performing its *formal analysis*; *obtaining funds* from the Agencia Nacional de Promoción de la Investigación, el Desarrollo y la Innovación (National Agency for the Promotion of Research, Development and Innovation); conducting the *necessary research* for the production of knowledge; proposing the work *methodology; managing* the project and the *resources* needed for its development; *supervising* the work of the entire research team and *validating* its results; *writing the* original draft and collaborating in the final *revision and editing*.

José BIURRUN MANRESA collaborated in the *formal analysis of* the document; proposed part of the *work methodology*; supervised *statistical work on data and results*; participated in the *validation* of the results and in the *review and editing* of the final document.

Abelardo DEL PRADO made his contributions in the research and conceptualization of the social dynamics implemented in this work. He also proposed the *methodology used* to obtain the socioeconomic information involved in the system's dynamics. He also supervised the work of the interviewers team and collaborated in the *writing of the original draft*.

H. Leonardo RUFINER collaborated with the *conceptualization* of the work and its *formal analysis*. He participated in *obtaining funds* from the Agencia Nacional de Promoción de la Investigación, el Desarrollo y la Innovación (National Agency for the Promotion of Research, Development and Innovation); directed the *research* needed for the production of knowledge; took part in the discussions to establish the *work methodology* and collaborated in the *validation* of the results along with the *writing of the* original draft and the final *revision and editing*.

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APPENDIX A: VALUES OF THE MAIN PARAMETERS OF THE MODEL

A.1 State transition matrices of the set of Hidden Markov Models

The values in Table A.1.1 to A.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 and those corresponding to neighborhoods with a low SBNI, on the right. Given that the behavior of each agent changes according to the time slot and the age range, it is shown how these Markov matrices change chronologically depending on the changes in people's mobility of, which are mainly influenced by the changes in the isolation and distancing phases that were verified during the year under study (2020).

FEBRUARY-MARCH-2020 (PRE-PANDEMIC)

Children-Area 2

Time slot 0	Home	Work / Study	Leisure	Others
Home	75	850	50	25
Work / Study	25	900	50	25
Leisure	25	900	50	25
Others	25	900	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**
Home	900	50	25	25
Work / Study	550	300	100	50
Leisure	800	10	95	95
Others	800	10	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**
Home	175	550	250	25
Work / Study	50	850	75	25
Leisure	200	350	400	50
Others	200	350	300	150

Children-Area 11

Time slot 0	Home	Work / Study	Leisure	Others
Home	275	650	50	25
Work / Study	25	900	50	25
Leisure	225	700	50	25
Others	225	700	50	25
Time slot 1	**Home**	**Work / Study**	**Leisure**	**Others**
Home	850	100	25	25
Work / Study	550	300	100	50
Leisure	750	60	95	95
Others	750	60	95	95
Time slot 2	**Home**	**Work / Study**	**Leisure**	**Others**
Home	150	525	300	25
Work / Study	50	850	75	25
Leisure	175	325	450	50
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
	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
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 A.1.1: transition state 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 (multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

JUNE 2020

	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**
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
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
	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 A.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 (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
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
	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 / 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
	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 A.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 (multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

	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
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 / 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
	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
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 A.1.4: transition state matrices of the set of Hidden Markov Models for the different sections as of October-2020. The values shown correspond to each transition probability (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

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 /**	**Leisure**	**Others**	**Time slot 2**	**Home**	**Work /**	**Leisure**	**Others**

		Study					Study		
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
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
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 A.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 (multiplied by the value 1000) based on age ranges, time slots and changes of location/activity considered.

A.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 of the hidden states corresponding to the states "Leisure" and "Others" are shown below.

Table A.2: Output emission matrices for the states “Leisure” and “Others” of the set of Hidden Markov Models used for the simulations.

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	60	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	60	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	cafe	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

A.3 Variation of parameters of Table 1 according to the date

Since some of the values of the model parameters depend on the isolation or distancing phase changes, the following shows how they change according to the time of the year in which the simulation is run and the corresponding provisions (2020).

Table A.3: Variation of parameters of Table 1 according to date and changes in the isolation or distancing phases (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

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