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Multi-agent simulation model for the evaluation of COVID-19 transmission

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ABSTRACT

This work proposes an agent-based model to analyze the spread processes of the COVID-19 epidemics in open regions and based on hypothetical social scenarios of viral transmissibility. Differently from other previous models, we consider the environment to be a multi-region space in which the epidemic spreads according to the dynamics and the concentration of agents in such regions. This paper suggests that software agents can provide a more suitable model for individuals, and their features, thus showing the influence of civil society in the context of pandemic management. This is achieved by modeling an individual as an agent with a wide range of features (health condition, purchasing power, awareness, mobility, professional activity, age, and gender). The model supports the design of populations and interactions akin to real-life scenarios. Simulation results show that the proposed model can be applied in several ways to support decision-makers to better understand the epidemic spread and the actions that can be taken against the pandemic.

1. Introduction

Currently, the world is experiencing the coronavirus disease (COVID-19) pandemic: an acute respiratory syndrome, caused by the SARS-CoV-2 virus. According to the World Health Organization (WHO), the rapidly growing outbreak of COVID-19 was originated from the city of Wuhan, Hubei Province, China in December 2019 [1]. On January 2020, the pathogen was identified, human-to-human transmission was reported soon after, and by April 2020 the outbreak had become the COVID-19 pandemic [1].

The virus that causes COVID-19 spreads easily among people, and more continues to be discovered over time about how it spreads. Data has shown that it spreads mainly from person to person among those in close contact (within about 6 feet, or 2 m). Although most people with COVID-19 have mild to moderate symptoms, the disease can cause severe medical complications and lead to death. The unavailability of diagnostic reagents for COVID-19, along with changes in surveillance intensity and case definitions, puts an overwhelming pressure on healthcare systems [2].

During the pandemic, there are multiple priorities, including the need to understand the disease spreads. This is important to prevent further transmission and optimize patient care. In fact, there is a large scientific literature on modeling epidemic spread. The susceptible-

infectious-susceptible (SIS) and the susceptible-infectious-recovered (SIR) are the most extensively studied models [3]. However, such analytic models are not well suited to represent COVID-19 since they: (i) assume individuals to be homogeneous and well mixed in the populations, and; (ii) neglect individuals heterogeneous social interactions and mobility patterns.

When modeling the spread for COVID-19, individuals cannot be treated as homogeneous. For instance, older adults are more likely to get severely ill from COVID-19. Moreover, adults of any age with some medical conditions (e.g. cancer, diabetes, coronary artery disease, cardiomyopathies and hypertension) are also more likely to get severely ill from COVID-19. In addition, the diversity of human mobility patterns and individual behaviors have a significant influence on the spreading processes of infectious diseases [4]. COVID-19 is highly contagious [9], which has forced governments worldwide to implement policies to reduce the spread of the infection, such as lockdown, closure of non-essential commerce and educational institutions [10].

In this paper, we present an agent-based model (multi-agent system) to simulate and analyze the dynamics of COVID-19 infectious process. A multi-agent system is an organization of autonomous agents interacting with each other within a shared environment [5]. Agents are heterogeneous entities used to model different individuals. The environment is the virtual representation of spaces (or regions) in which agents are

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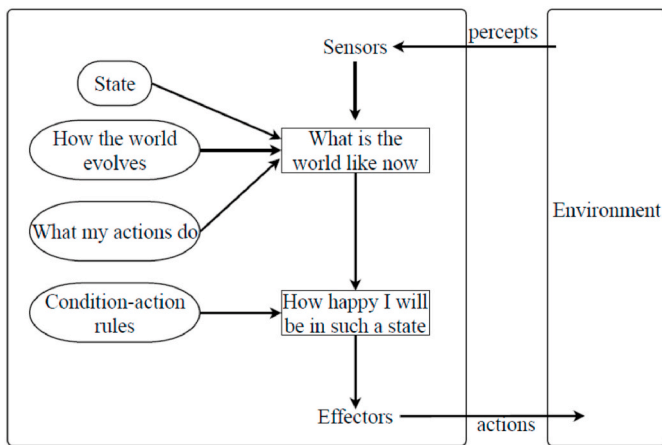


Fig. 1. Multi-agent modeling flowchart - [16].

located. Lastly, interaction is the motor dynamics in a multi-agent system – it models the interaction between agents and between an agent and the environment.

Differently from other works on modeling COVID-19 spread dynamics, the proposed model is able to represent individuals’ heterogeneity, environmental diversity and social interaction. An agent has several features to express age, comorbidities, disease presentation (asymptomatic, mild or severe) among others. The environment can be divided into regions with specific purposes (e.g. commerce, educational, open public space), providing different constraints in social interactions, i.e. providing semantics to limit social contact – it overcomes the simplification of the “one agent may randomly contact all”, since, in reality, it is most likely that an individual may not get in contact with just anyone. On the other hand, an individual is more prone to get a close contact with a co-worker, with someone who goes to the same store, or

someone who lives in the same residence, etc. These interactions are delimited by environment regions and agent features.

Also, the proposed model allows for the specification of constraints or rules for agents and interactions. For instance, it is able to model the conscious use of masks or the adoption of social distancing policies. These external restraints affect the COVID-19 contagious process and they are not well represented in existing works. Such works deal with binary solutions, i.e. lockdown or not, masks or not. They are not able to model targeted social distancing policies (e.g. stores may open, but educational facilities should close; some may use masks, while others may not). The proposed agent, environment and interaction design allows such specifications.

We validated the proposed agent-based model by simulating two different scenarios: with and without the use of social distancing policy. The simulations intended to follow the evolution of the susceptible, infected, deceased, and recovered population in each proposed scenario. From the experimental results we found that the proposed agent-based model is suited to describe the COVID-19 epidemics spread with individual, social and regional parameters. The results also show that not all of the susceptible agents in the simulation are infected due to the mobility of agents.

The remainder of this paper is structured as follows. Section 02 presents related work research on investigating and developing epidemiological models. Section 03 introduces the proposed model, including the aspects and attributes that define the behavior of the agents and the environment. Next, we present the model implementation, which presents the procedures used for to develop the simulator that uses the proposed model. The experimental results describe the evaluation, consistency, and validation of two experiments t. Finally, we present the conclusions for this work.

2. Related work

Epidemiological models try to reproduce the dynamics of an

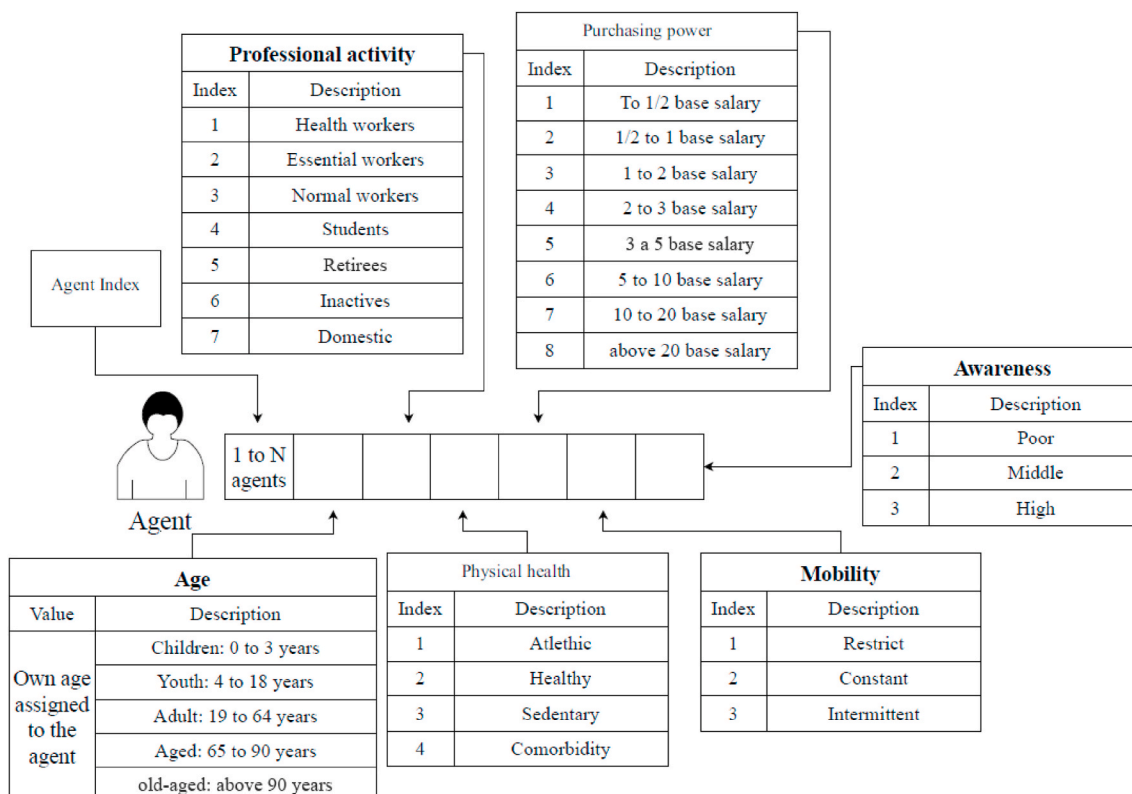


Fig. 2. Classification of the attributes according to their respective aspects for the elaboration of the matrix that stores the agents’ attributes in the model.

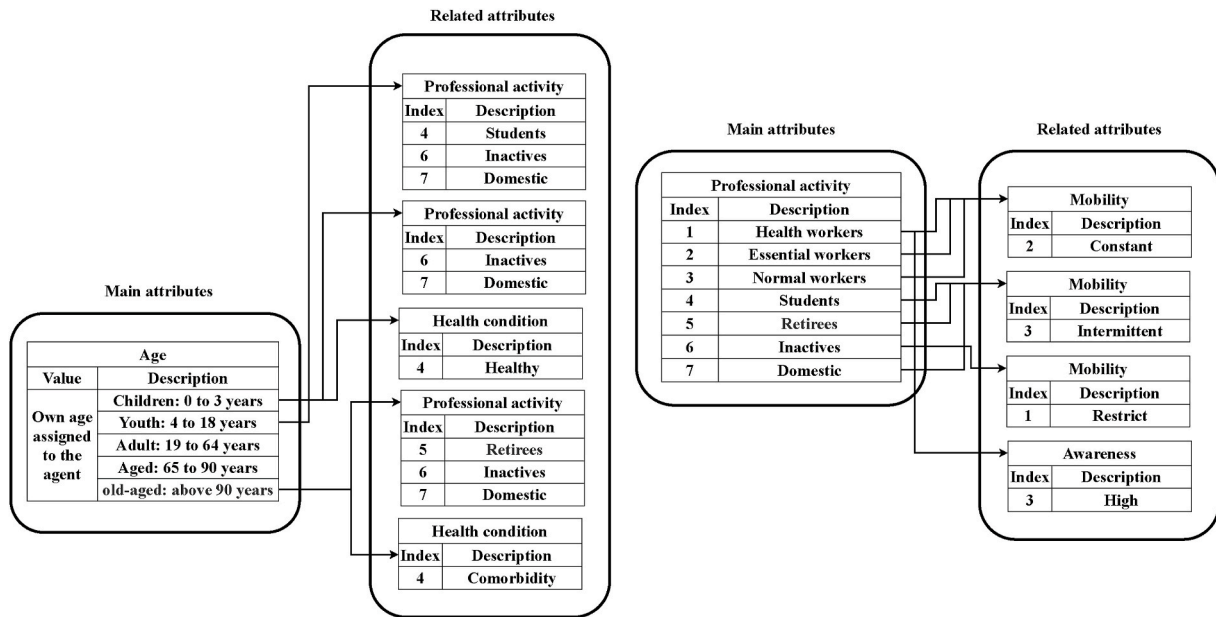


Fig. 3. Attributes and hypotheses related to the agents' age and professional activity classification.

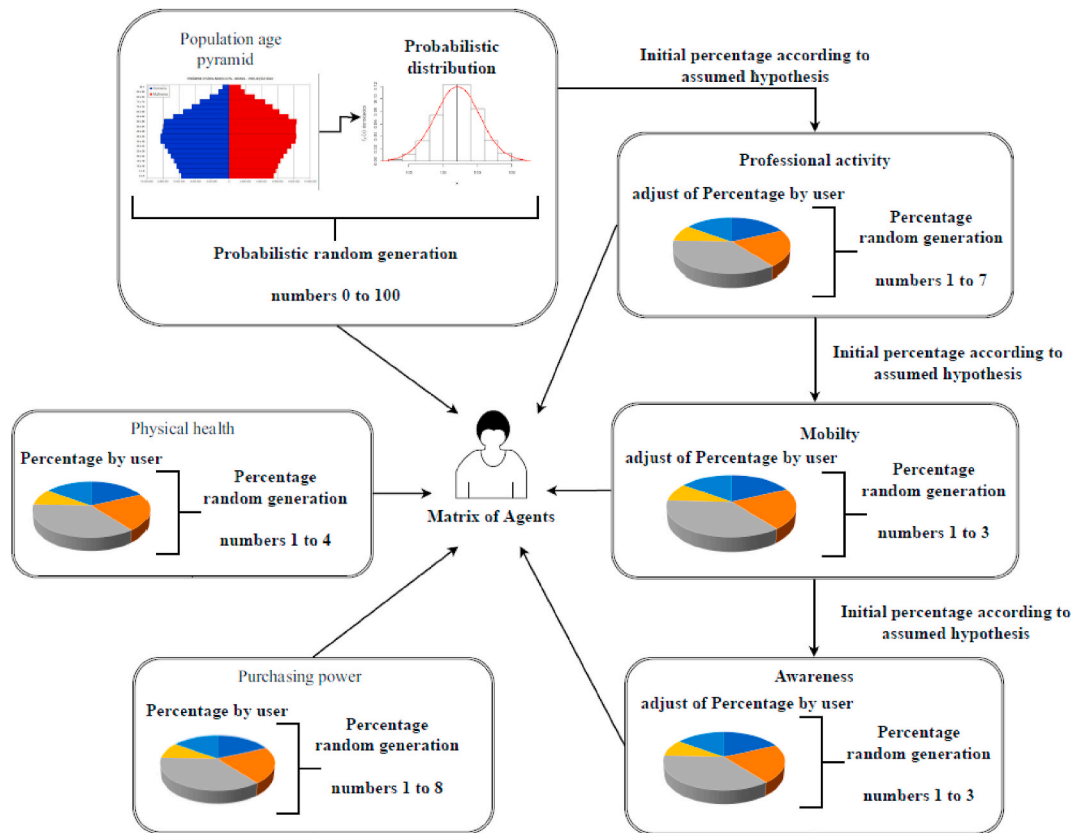


Fig. 4. Attribute classification process and agent attributes matrix elaboration.

epidemic spread in terms of the evolution of the total number of infected, susceptible, deceased, and recovered subjects over a given period of time. Such models intend to provide relevant information to investigate/predict the behavior of the pandemic and they are usually based on a set of ordinary differential equations or stochastic modeling. In the following subsections we present works that aim to model the dynamics of the COVID-19 spread, dividing them into two categories: analytical

models and agent-based models.

2.1. Analytical model studies

According to Ref. [6], an analytical model is primarily quantitative or computational in nature and represents the system in terms of a set of mathematical equations that specify parametric relationships and their

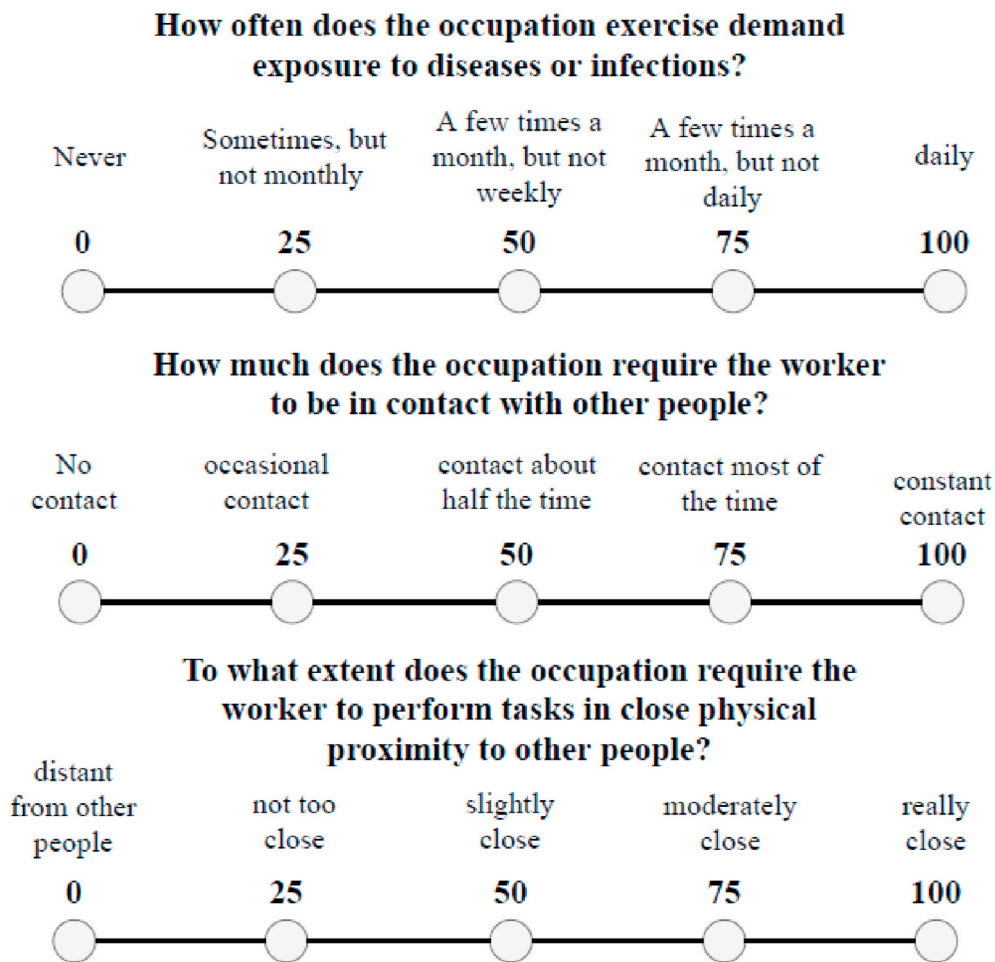


Fig. 5. Quantification of the risk of infection of COVID-19 according to the methodological note of the work [25].

associated parameter values as a function of time, space, and/or other system parameters. Equations that are defined in the model must provide a precise representation of the system and environment to meet the purpose of the model. This is done by modeling the underlying phenomena to predict or assess how well the system performs.

Several works ([7–10]) on modeling the COVID-19 epidemic dynamics use the Susceptible-Exposed-Infectious-Removed (SEIR) Model, but with limited scope. The work in Ref. [7] makes several simplifications regarding the dynamics and the complexity of the relationships among individuals. The work in Ref. [8] shows that restrictions to population mobility, including closing schools, cancelling presential meetings and embracing remote work should be considered to lower transmission rates. Their work analyzed the epidemic in Wuhan, China. The work in Ref. [9] analyzed the data available at the Tracking COVID-19 initiative of the Center for Systems Science and Engineering at Johns Hopkins University and their results show that the recovery time parameter is almost independent from the epidemic region/country, whereas the infection and mortality rates are more dependent on the region/country.

The work presented in Ref. [10] used the SEIR-HC model, an evolution of the SEIR model with two different social circles. To better explore the transmission dynamics of COVID-19, a two-step optimization method was applied in order to estimate the parameters of the SEIR-HC model. Consequently, the results on the propagation behavior of COVID-19 were consistently reproduced, even without sufficient observation data.

The work in Ref. [11] is based on the SIR model, and it tried to characterize the similarities and differences between the propagation

behaviors of the COVID-19 pandemic in several countries, highlighting the heterogeneous character of the propagation of this pandemic in Brazil. The relevant contribution of that work consists in using the global average of the infection rates, recovery time and mortality rate of this pandemic.

To evaluate the spread dynamics of COVID-19 in a ship, the work in Ref. [12] made an adjustment to the data by applying a gamma probability distribution together with the *earlyR* package to estimate the reproductive number of the pandemic (R_0) of its initial phase. However, that work presented some limitations due to the limited number of individuals in the population on board, the high transmissibility of COVID-19 and the rapid increase in the number of infected cases, which consequently contributed to a significant drop in the proportion of the susceptible population.

In [13], a Bats-Hosts-Reservoir-People (BHRP) transmission network model was developed to simulate the potential transmission from the source of infection (probably bats) to human infection. The research focused on the transmission of the Huanan Seafood Wholesale Market (reservoir), simplifying the Reservoir-People (RP) transmission network model. Thus, the study was very limited and the initial reproductive number of the pandemic (R_0) was calculated based on the RP model to assess the transmissibility of SARS-CoV-2.

The study conducted by Ref. [14] proposes the SIDARTHE model, which discriminates between infected individuals depending on whether they were diagnosed and the severity of their symptoms. The distinction between diagnosed and undiagnosed individuals is important because the former are usually isolated and therefore less likely to spread the infection. With the results obtained, the model demonstrated

Table 1
Scores assigned to each aspect of agents' attributes.

Professional activity		
Index	Description	Weigth
1	Health workers	75.39
2	Essential workers	62.98
3	Normal workers	59.13
4	Students	58.71
5	Retirees	54.12
6	Inactives	52.07
7	Domestic	52.07

Purchasing power		
Index	Description *	Weigth
1	up to 1/2	60
2	1/2 to 1	55
3	1 to 2	50
4	2 to 3	45
5	3 a 5	40
6	5 to 10	35
7	10 to 20	32
8	above 20	30

Physical health		
Index	Description	Weigth
1	Athletic	30
2	Healthy	25
3	Sedentary	45
4	Comorbidity	50

Mobility		
Index	Description	Weigth
1	Restrict	20
2	Constant	60
3	Intermittent	40

Awareness		
Index	Description	Weigth
1	Poor	60
2	Middle	40
3	High	20

* using minimum wage as base

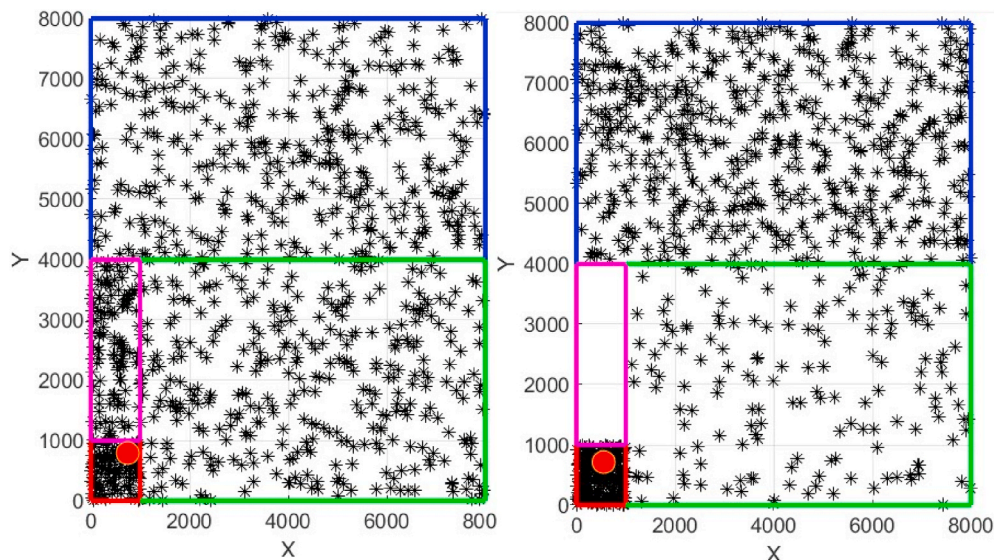


Fig. 6. Example of environment model - without social distancing (left) and with social distancing (right). Red agents are infected.

that restrictive social distancing measures should be combined with generalized testing and contact tracing to end the COVID-19 pandemic.

In general, the main disadvantages of analytical studies used to model COVID-19 dynamic spread are that: they assume population size is constant, meaning that those models do not consider the mobility of people; they assume individuals are homogeneous, which means that

models neglect the heterogeneous social interaction, the mobility patterns and the different behavior of individuals. In this sense, agent-based models in which agents may be modeled as different individuals and may be mobile, tend to be more adequate for representing the COVID-19 dynamics.

The interface is titled 'Create the matrix of agents attributes', 'Create the weighted matrix', and 'Model Process'. It features the logo of the Instituto Militar de Engenharia (IME) and the text 'EXERCÍCIO BRASILEIRO INSTITUTO MILITAR DE ENGENHARIA'. Key input fields include:

- Number of agents:** 500
- Number of infected:** 1
- Days of Panemic:** 150
- Population age group file:** Age step: 5
- Health condition of agents:** Total: 0, Athletic (%): 9, Healthy (%): 29, Sedentary (%): 43, Comorbidity (%): 19.
- Initial position and probabilities:** Healthcare professionals location probabilities (Cumum area: 35, Hospital: 45, Schools: 5, commerce and i...: 15, Total: 0), Students professionals location probabilities (Cumum area: 45, Hospital: 5, Schools: 35, commerce and i...: 15, Total: 0), Inactive location probabilities (Cumum area: 60, Hospital: 20, Schools: 5, commerce and i...: 15, Total: 0), Autonomous professionals location probabilities (Cumum area: 45, Hospital: 5, Schools: 15, commerce and i...: 35, Total: 0), Essential location probabilities (Cumum area: 35, Hospital: 15, Schools: 10, commerce and i...: 40, Total: 0), Normal location probabilities (Cumum area: 40, Hospital: 5, Schools: 10, commerce and i...: 45, Total: 0), Retirees location probabilities (Cumum area: 45, Hospital: 15, Schools: 10, commerce and i...: 30, Total: 0).
- Percent of purchasing power of the population:** Total: 0, 1/2 to 1 minimum wage: 4.92, 1/2 to 1 minimum wage: 13.33, 1 to 2 minimum wage: 39.38, 2 to 3 minimum wage: 16.1, 3 to 5 minimum wage: 11.6, 5 to 10 minimum wage: 8.27, 10 to 20 minimum wa...: 4.07, up to 20 minimum w...: 2.35.
- Percent of work occupation:** Total: 0, Healthcare professionals (%): 3.2, Essential workers (%): 10.4, Regular workers (%): 47.6, Retirees (%): 6, Domestic (%): 7.9, Inactives (%): 4.4, Students (%): 20.5.
- Environment Inputs:** Environment distance: 2000, Contagious distance: 1, Social policy: NO.
- Awareness attribute probabilities:** Total: 0, High: 35, Intermediate: 45, Low: 20.

Fig. 7. Input parameters' interface.

2.2. Agent-based model studies

Agent-based models are composed of societies of software agents that are able to interact with each other. A software agent (or just agent) is a computer program which works toward goals (as opposed to discrete tasks) in a dynamic environment (where change is the norm), without continuous direct supervision or control, and exhibits a significant degree of flexibility [15]. According to Ref. [5], an agent is defined by the following properties: (ii) autonomy (agents perform most of their actions without direct interference from human agents or other computational agents, having total control over their actions and internal state); (ii) social ability (ability to solve certain problems or for other convenience, interact with other agents, to complete the resolution of their problems, or to assist other agents); (iii) reactivity (perceive and react to changes in the environment in which they are inserted), and; (iv) proactivity (ability to deliberate instead of just reacting in response to changes in their environment. Fig. 1 (from Ref. [16]) illustrates how an agent interacts and reacts to the environment it is immersed in.

Some characteristics of an agent-based model include [5]: each agent can act autonomously within the modeling environment; there are no complex equations or formulations that control the global model; they are capable of modeling complex systems in which they incorporate variables that are difficult to implement by analytical models, and; the data and results are decentralized. Agent-based models have been used in several applications, such as urban traffic intensity [17,18], simulation of anti-terrorism actions [19], evacuation simulations [20] and multi-criteria decisions in the financial market [21,22].

Agent-based models have also been used to model pandemic dynamics. The works in Refs. [23,24] describe the state-of-the-art in epidemiological computing and state that agent-based systems can significantly contribute in applications in this area. They discuss some of the main problems in epidemiology, which can be solved using

agent-based techniques and their challenges.

In [25], the authors define a database that seeks to quantify the risk of infection by COVID-19, according to the various attributes of professional activity, purchasing power, mobility (proximity among people) and other attributes. That work can be used as a methodological basis for the distribution of these attributes among agents and for the parameterization of infection, recovery time and death probabilities of the agents.

The work in Ref. [26] presents an agent-based model to simulate the spread of the influenza pandemic (new H1N1) in Egypt, in which agent interactions took place in a space-time context. The proposed model involves different types of parameters such as: attributes of the social agent, distribution of Egypt's population, and patterns of agent interaction. In addition, the proposed model was used to measure the effectiveness of different control strategies to intervene in the spread of the pandemic.

In [27], the authors present an agent-based model that demonstrates that geographic characteristics defined by the purchasing power can affect the health of individuals. The effects arise from complex interdependent processes in which individuals interact with each other and their environment and in which both individuals and environment adapt and change with time. However, traditional epidemiological studies and statistical regression approaches are unable to examine these dynamic processes.

The work in Ref. [28] developed an agent-based model to evaluate the spread dynamics of COVID-19 in a given population of agents. The behavior of each individual was characterized by a set of simple rules, which considered their basic interactions (their degree of autonomy). Each agent was configured with different mobility requirements and infection probability. Thus, several possible scenarios could be tested to obtain the behavior profile of the pandemic. However, this work does not include the recovery of agents in the model. In this sense, once an

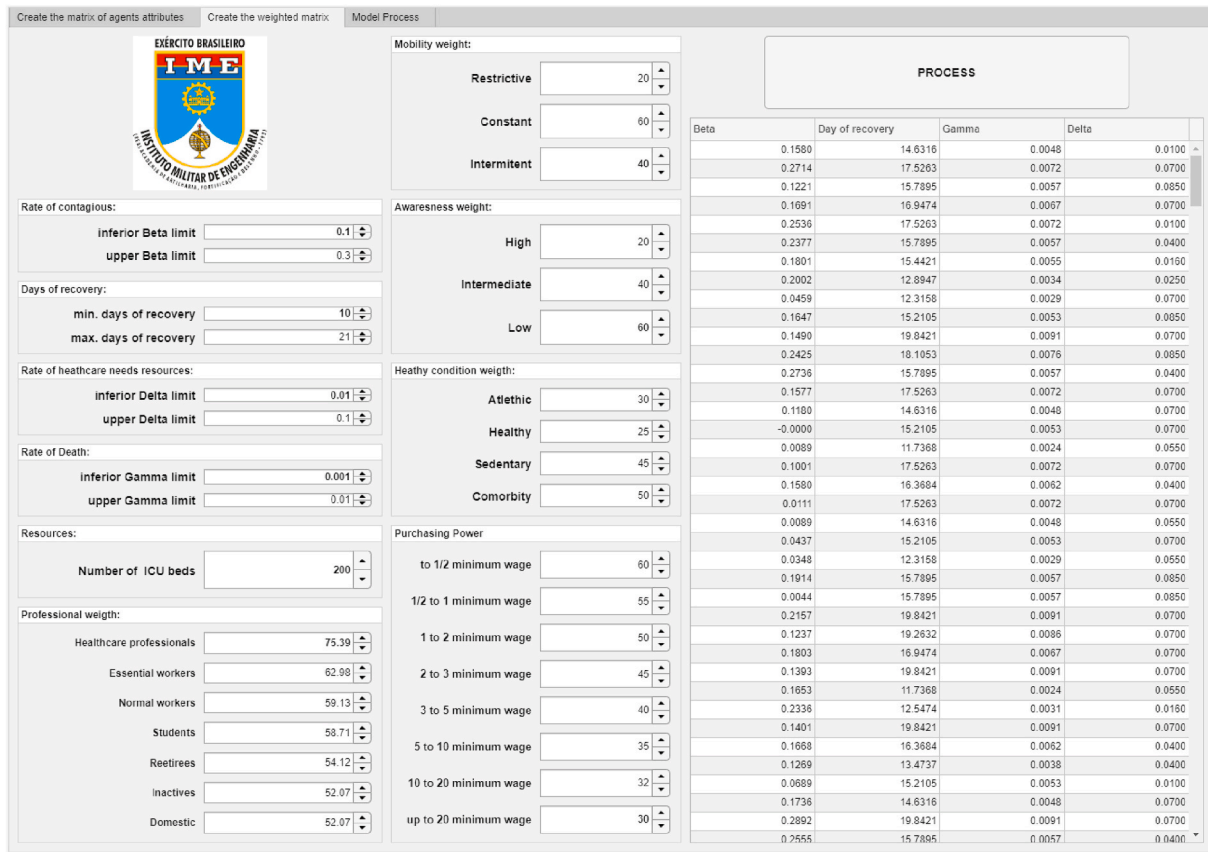


Fig. 8. Setup's interface of weights and agents' infection, deceasing and recovering probabilities.

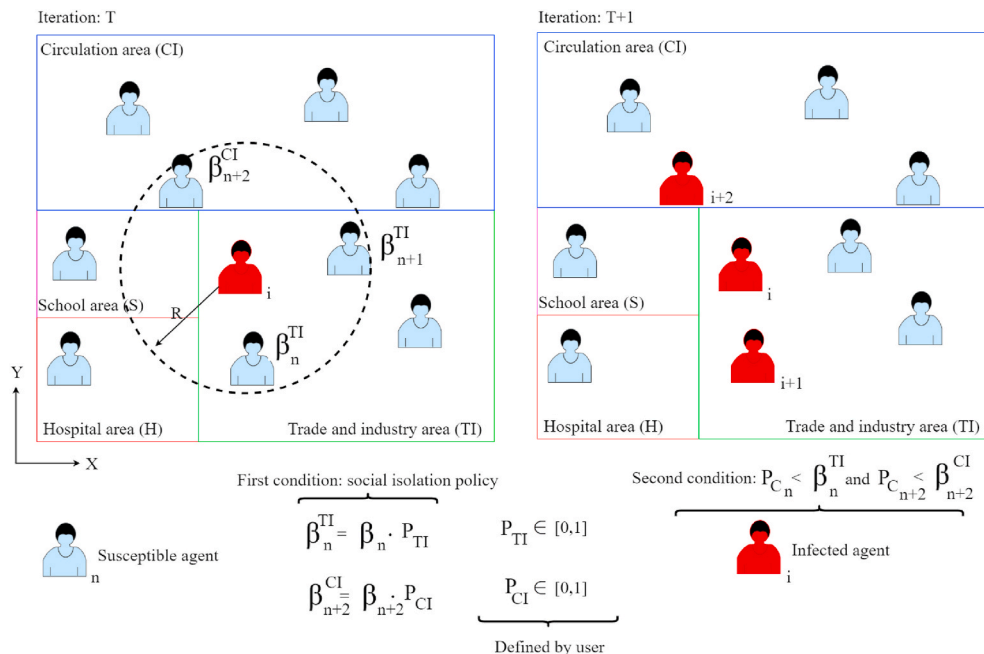


Fig. 9. Illustration of the application of rule 1 - infection of agents.

agent was infected, it could infect other agents indefinitely. It also lacks important individual parameters, such as age, economic conditions, profession and level of awareness. These parameters influence the actions (i.e the mobility, interactions, etc) of agents and they are important to provide more accurate scenarios of the pandemic spread. It also only

considered just one environment in the model, which is far from the reality of the affected societies.

This work presents an agent-based model to analyze the spread processes of the COVID-19. It differs from the above-mentioned studies since it considers the existence of different regions in the environment

Table 2
Probability of presence of agents in a given area (or environment) within the model.

Index	Area	Health workers		Essential workers		Regular workers		Students	
		without social isolation	with social isolation	without social isolation	with social isolation	without social isolation	with social isolation	without social isolation	with social isolation
1	Circulation area	35%	45%	35%	45%	40%	80%	45%	80%
2	Home and industry	15%	10%	40%	25%	45%	15%	15%	15%
3	Medical facility	45%	45%	15%	30%	5%	5%	5%	5%
4	Workplace and school	5%	0%	10%	0%	10%	0%	35%	0%

Index	Area	Retirees		Inactives		Domestic	
		without social isolation	with social isolation	without social isolation	with social isolation	without social isolation	with social isolation
1	Circulation area	45%	65%	60%	65%	45%	75%
2	Home and industry	30%	20%	15%	10%	35%	20%
3	Medical facility	15%	15%	20%	25%	5%	5%
4	Workplace and school	10%	0%	5%	0%	15%	0%

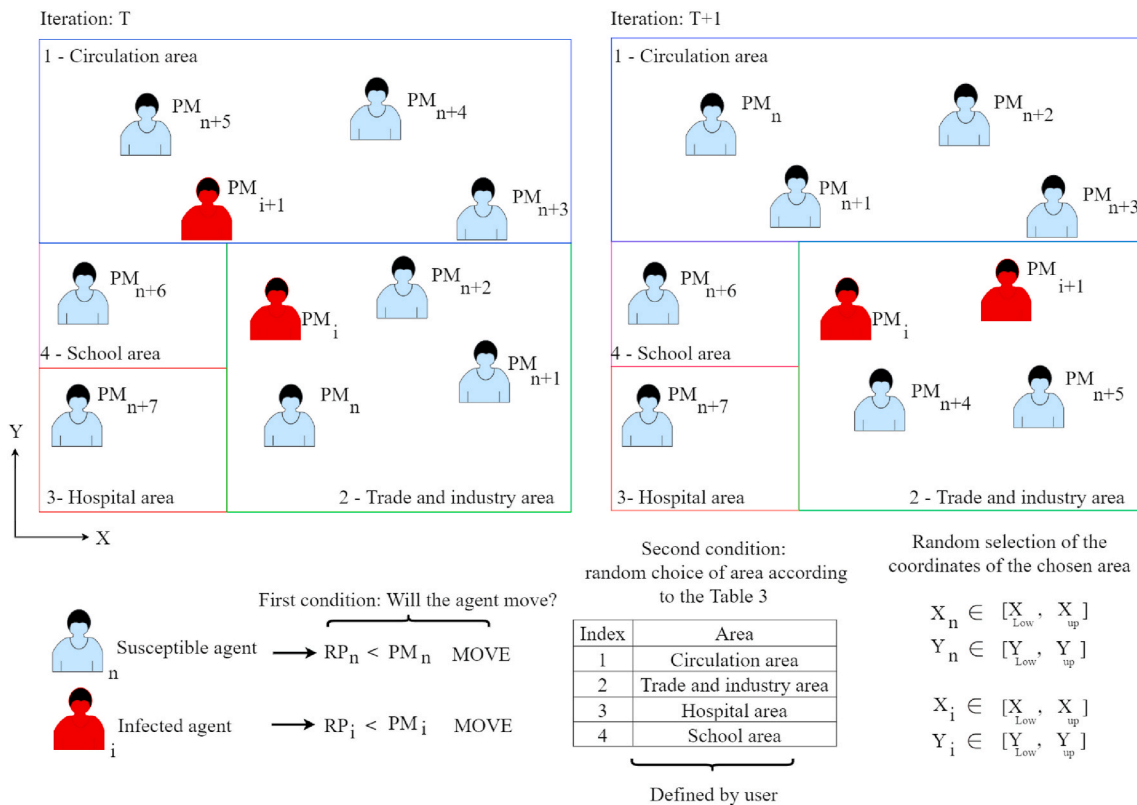


Fig. 10. Application of rule 2 - movement of agents between the areas (or environments) of the model. Rule 3 - Agent Deceasing and Recovering.

(e.g. home, work, commerce site, school) and some specific characteristics in the current scenario (e.g. social distancing, awareness).

3. The proposed model

This section presents our proposed agent-based model to analyze the spread processes of the COVID-19 epidemics in open regions and based on hypothetical social scenarios of viral transmissibility. We borrowed the notions of simple rules of movement, proximity among the agents, probability of infection and evolution of the states (or stages) of the disease in the agents from the work in Ref. [28].

However, the proposed model implements several other important characteristics of COVID-19 epidemic spread scenarios. It models

exogenous control measures to reduce spread (social distancing policies), it also models physiological and socioeconomic differences between individuals in the same population. Therefore, each agent has its own: (i) probability of contracting the disease; (ii) rules of movement; (iii) recovery time, and; (iv) probability of death. Moreover, the proposed approach allows for agents to move between different types of region in the environment, with different infection exposures. We understand that these notions bring the model closer to COVID-19 real-life scenarios.

We considered epidemic spread in several regions (limited parts of the agent environment), in which there is a variable number of agents at time t . Each individual agent is in one of four states: susceptible; infectious; recovered, or; deceased. A susceptible agent can enter the



Fig. 11. Application of rule 3 - death or recovery of agents.

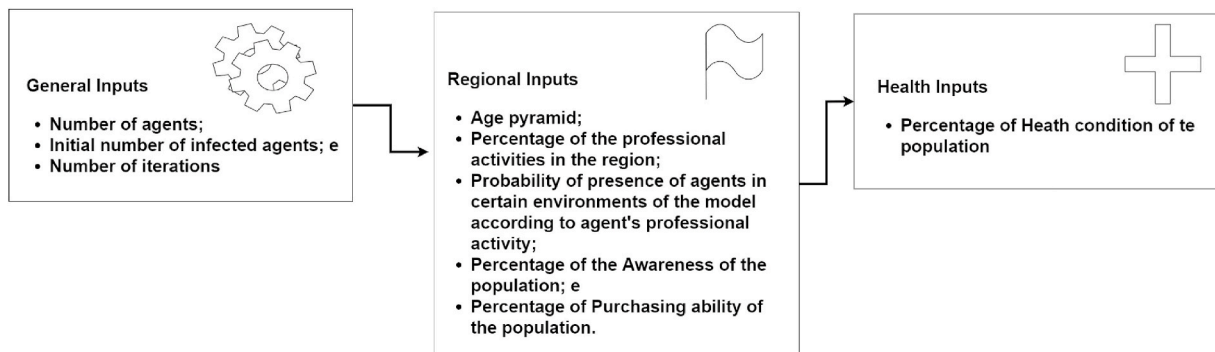


Fig. 12. Entries that the user must configure (according to the region to be analyzed) for processing.

infectious state when infected by infectious individuals. After a period of time, the infectious individuals will either recover due to the body immunity or pass away, entering the deceased state. The agents in recovered state are assumed not to be infected any more. Every change in state depends on a given average probability.

3.1. Agent and environmental parameters

We initiated the modeling by defining scenario parameters, i.e. those parameters that will be use to discriminate different agents and regions

in the environment. These are the basic initial parameters that should be set to define the distribution of the population, and include physiological and socioeconomic aspects. The parameters are described below:

3.2. Agent parameters

Age: this parameter is important since most of the people who evolve to the acute form of the disease and, thus pass away, are of higher ages.

Physical health: this parameter is important since it models the existence of medical preconditions and comorbidities, which increase

Table 3
Input of the percentages of agent population distribution for the classification of their respective.

General Parameters:	Value	Unity	Purchasing power:	%	Number of Agents
Number of Agents	500	Num.	up to 1/2 minimum wage	4.92%	49
initial Number of Infected	1	Num.	from 1/2 to 1 minimum wage	13.33%	133
Models Iteration	150	days	from 1 to 2 minimum wage	39.36%	394
			from 2 to 3 minimum wage	16.10%	161
			from 3 to 5 minimum wage	11.60%	116
Professional activity:	%	Number of Agents	from 5 to 10 minimum wage	8.27%	83
Healthcare Professional	3.20%	32	from 10 to 20 minimum wage	4.07%	40
Essential Workers	10.40%	104	above 20 minimum wage	2.35%	24
Regular Workers	47.60%	476			
Students	20.50%	205	Awareness:	%	Number of Agents
Retirees	6.00%	60	Low	20%	200
Inactives	4.40%	44	intermediate	45%	450
Domestics	7.90%	79	high	35%	350
			Physical Health	%	Number of Agents
Mobility:^a	%	Number of Agents	Athletes	9.00%	90
Restricted	5.20%	52	Healthy	29.00%	290
Constant	64.40%	644	Sedentary	43.00%	430
Intermittent	30.40%	304	Comorbidity	19.00%	190

^a The percentages presented for the mobility attribute were based on the classification of the agent’s professional activity.

the probability of an agent to develop an acute form of the disease.

Mobility: this parameter is important since the disease is transmissible through proximity to contaminated agents, and the more mobile an agent is, the more likely it is to get infected.

Professional activity: this parameter indicates which type of regions the agent may be at (e.g. an agent who is a receptionist or a physician has a higher probability to go to a hospital or clinic - thus being more exposed to infection - instead of being an agent who is an architect, with lower probability to go to a more exposed region).

Purchasing power: this parameter is important since it defines if the agent is more likely to have access to prevention items (e.g. masks, running water to wash hands) or treatment in private medical facilities.

Awareness: the agent’s degree of awareness may make it less susceptible to the infection. Agents with higher levels of awareness have more social empathy (e.g. wear masks, avoid crowds, wash their hands). In the proposed model, an agent with 4 or less years of age inherits the value for this parameter from its parents, as it is not able to discern about this condition.

3.3. Environmental parameters

Type risk: this parameter is important since it is used to differentiate the risk of infection for each region (e.g. a hospital, a shopping, a factory

plant may present more risk than a home or private office).

Crowd level: this parameter is important since it defines the allowed concentration of agents in a given region. The more crowded a region is, the higher its infection risk.

The set of the values used in the proposed model for the parameters presented above were based on the score and on the database presented in Ref. [25]. That work poses an a relevant contribution, consisting of a methodological panel of risk scores for COVID-19 depending on the attributes of individuals in a population, whose quantification was done by crossing a series of data from different sources and databases. Fig. 2 shows the possible values to the proposed model different attributes.

It is known that some attributes are co-related, such as professional activity and mobility. For instance, if an agent gets “essential” as the professional activity value, it may not have its mobility restricted. The co-relations adopted in this work is shown in Fig. 3. Other assumptions about the model parameters include: (i) any agent can be considered inactive or domestic, regardless of their age; (ii) agents from 0 (zero) to 3 years of age are always classified as inactive or domestic; (iii) agents under 18 and over 3 years of age are classified as students (except for those previously classified as inactive or domestic); (iv) agents over 90 years of age can only be classified as inactive, domestic or retired; v health, essential or normal work agents must have constant mobility; vi retired, domestic and students agents must have intermittent mobility; (vii) inactive agents or agents that are 90 years of age or older must have restricted mobility; (viii) agents that are 90 years of age or older have comorbidities; (ix) agents under 4 years of age are healthy, and; (x) health workers have high awareness.

The age of an agent is the main driver for the probabilistic distribution of other parameters. Hence, it is important to analyze the population age pyramid of the simulated scenario case to properly randomize the parameter value distribution among the agents. Fig. 3 shows an example of parameter value distribution according to a population age pyramid. As for the purchasing power attribute, its values were distributed according to the data provided in Ref. [25]. Fig. 4 shows the detailed process of classifying the attributes.

3.4. Quantification and classification of attributes

The attributes define the behavior rules of the agents within in the model. In the same way as [25], we assigned a scale from 0 to 100 for the scores, according to the aspects attributed to the agents described in Fig. 2. Thus, it is known that for higher scores, the agent is more prone to present a behavior that corroborates his infection of the pandemic. Fig. 5 presents the quantification of the risk of infection by COVID-19 established in Ref. [25].

Based on the scoring procedure illustrated by Fig. 5 and the database published in Ref. [25], the distribution of scores among the attributes is presented in Table 1. The risk of infection score is based on the age attribute and the professional activity attribute.

3.5. Infection probability, recovery time and mortality of agents

This work uses the range of values established by the work [29] to calculate the probability of infection (β), recovery time (T_{rec}) and mortality rate (γ) based on the weights assigned to agents according to the classification of their attributes. The probability of infection (β) ranges from 0 to 0.3. For each agent n , fees were calculated using the following equations:

$$\beta_n = \frac{\text{age}(n) + \text{activity}(n) + \text{mobility}(n) + \text{awareness}(n)}{4} \quad (1)$$

$$T_{rec_n} = \frac{\text{physical health}(n) + \text{purchasing power}(n) + \text{awareness}(n)}{3} \quad (2)$$

$$\gamma_n = \frac{\text{physical health}(n) + \text{purchasing power}(n)}{2} \quad (3)$$

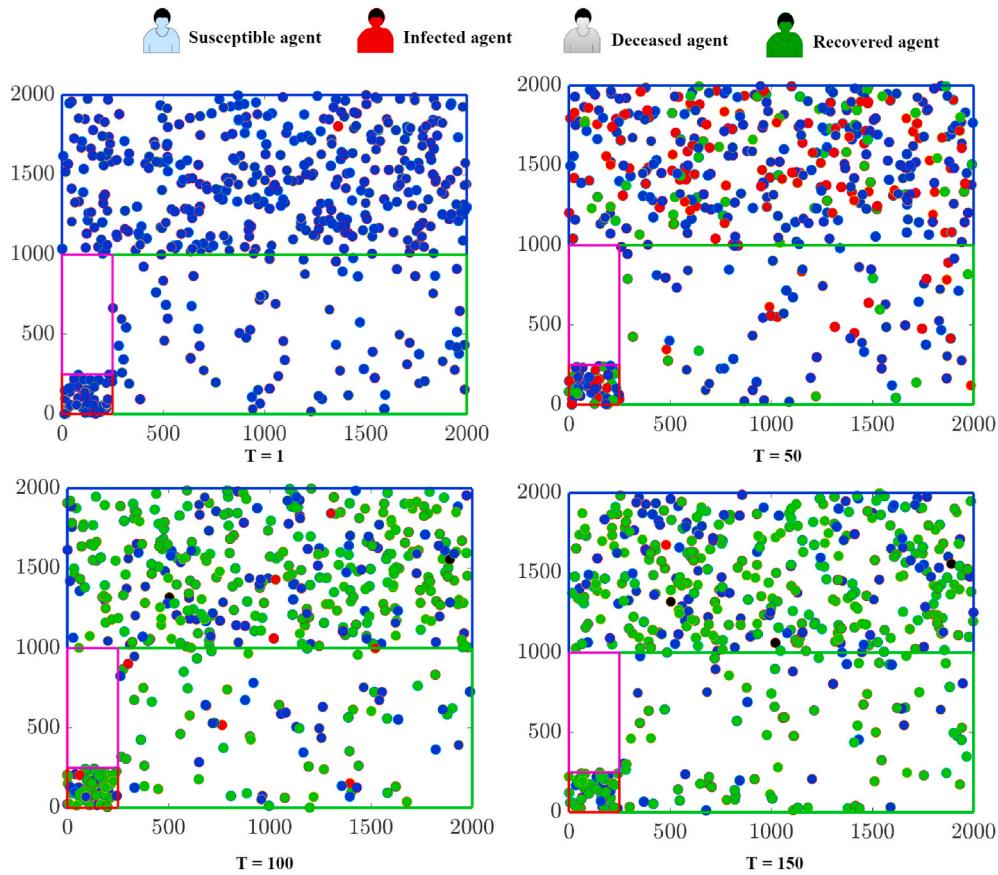


Fig. 13. Evolution of the multi-region scenario by iteration T , with social distancing policy.

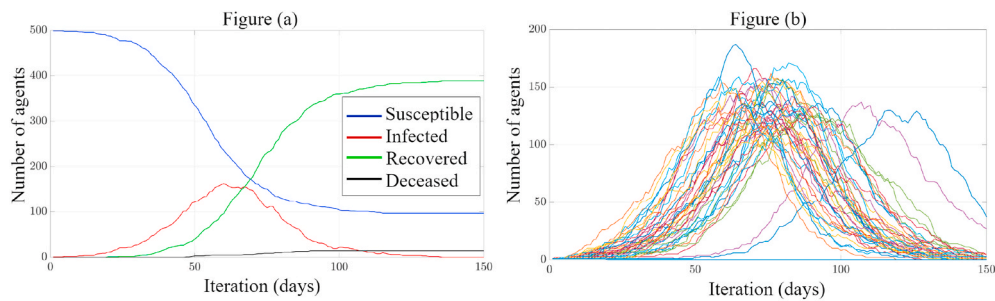


Fig. 14. (a) Typical response curve of the model in terms of the evolution of the number of susceptible, infected, deceased and recovered. (b) evolution curve of the number of infected by iteration of the 50 (fifty) processes of the model.

To calculate the value of β , first the average score for the agent is obtained, i.e. it follows a linear relationship between the average score obtained by each agent. The recovery time parameter (T_{rec}), was established periods from 10 to 21 days. Thus, the lowest average score obtained among agents will receive the T_{rec} for ten days and the highest average score will receive the T_{rec} for 21 days. So, it follows a linear relation for the other average scores. We chose the range from 10^{-4} a 10^{-2} for the γ .

3.6. Environment modeling

The proposed model considers four different regions in the agent environment. The main idea is to model high-level types of region: (i) circulation areas; (ii) homes and factories; (iii) workplaces and schools, and; (iv) medical facilities. Fig. 6 presents an example of the environment and its four regions (blue for circulation; green for homes; magenta for workplaces, and red for medical facilities).

The initial position of each agent in the environment is randomly determined. The actual position is represented by a coordinate. The mobility function of an agent is driven by its professional activity attribute and the social distancing policy adopted. This means that, for each professional activity, there will be a probability distribution of the presence of these agents in one of the environment regions. The details of such function are also presented in Section 4.

4. Model implementation: the M²CovidSim

To validate the proposed model, we developed a simulator in MATLAB named M²CovidSim to simulate a hypothetical epidemic spreading in a finite region environment, as shown in Fig. 6. Its user's interfaces are presented in Figs. 7 and 8. Our implementation was based on [28], and defined three main rules of movement.

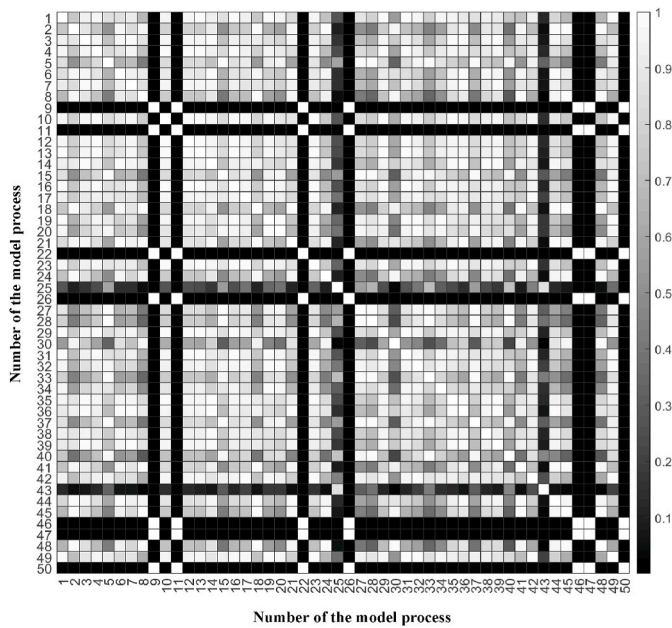


Fig. 15. Consistency/similarity evaluation matrix between the response curves of the number of infected of the processes of the model with social isolation.

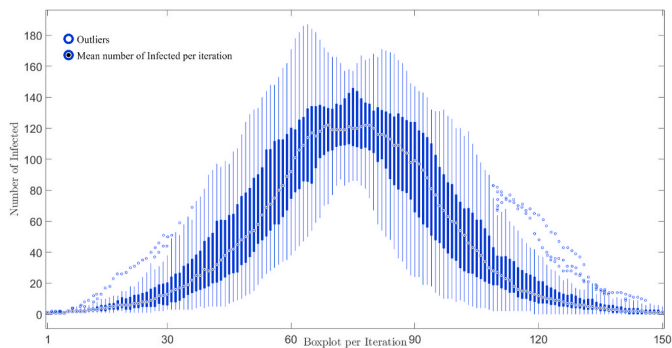


Fig. 16. Boxplot analysis of the number of infected by iteration of the model response curves.

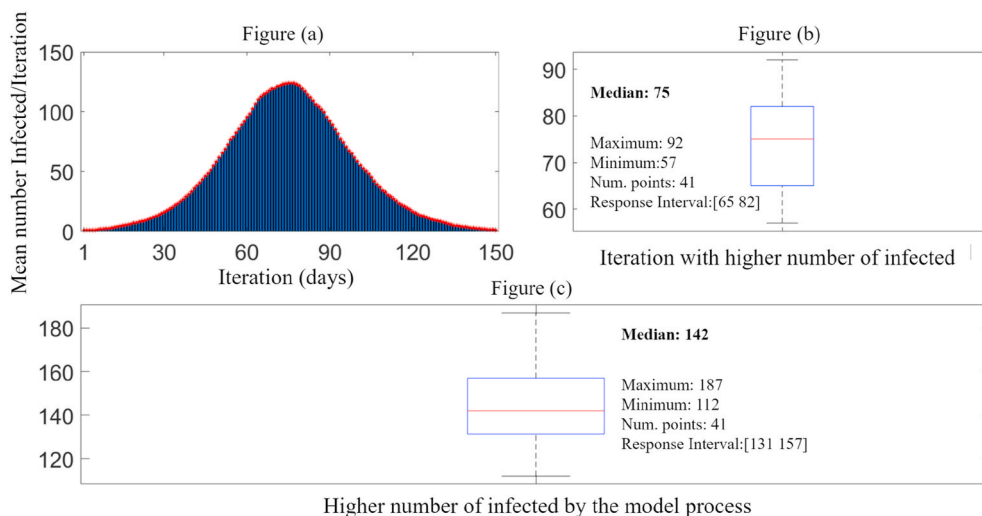


Fig. 17. (a) Graph with the averages per iteration of the number of infected agents in the model. (b) Statistical analysis of iterations containing the peak of the response curves. (c) Statistical analysis of the maximum number of infected agents at the peak of the curves.

4.1. Rule 1: infection

At the beginning of the agent-based simulation, all agents are positioned in the environment and one given agent is randomly chosen to be in the infected state. This is the patient zero. The infection rule uses the Euclidean distances among agents, which are compared to infection distance R defined by the simulation designer.

First, the model calculates the cluster of nearby agents of an agent (set of agents whose distance is lower or equal to R). We separate the non-infected (susceptible or recovered) agents in the cluster and we analyze the infection probability (β) for each of those agents. The infection probability calculation algorithm uses the type risk of the region in which the agent is. It also uses the social distancing policy, if determined. Once β of the non-infected agents in the cluster has been defined, the algorithm generates a probability $P_c \in [0, 1]$, as a random number $[0; 1]$ for each non-infected agent. If the P_c of a certain agent is smaller than its β_n , it will go to the infected state, otherwise it will remain in its current state. Fig. 9 illustrates the application of this rule.

4.2. Rule 2 - agent movement

The movement of an agent is determined by a probability calculated using the agent state. Equation (4) shows the movement probability of a susceptible or recovered agent and Equation (5) shows the movement probability for infected agents.

$$PM_n = \frac{\text{mobility}(i)}{100} \tag{4}$$

$$PM_i = \frac{\text{mobility}(i) \cdot \text{awareness}(i)}{100} \tag{5}$$

In each simulation interaction, the agent movement algorithm generates a random number $RP_n \in [0, 1]$, for each agent. If, for a given agent, this number is lower than PM_n , the agent will move, otherwise it will keep its position.

A movement indicates that an agent will switch regions. If an agent moves, the algorithm generates a random number from 1 to 4. This number represents the four existing regions in the environment: (1) circulation area; (2) home and industry; (3) medical facilities, and; (4) workplace and school. The function that generates this random number uses the restrictions imposed for an agent to be in one of the specified regions, which are determined by its professional activity and the social distancing policy, if determined. Table 2 presents the percentages defined in this work.

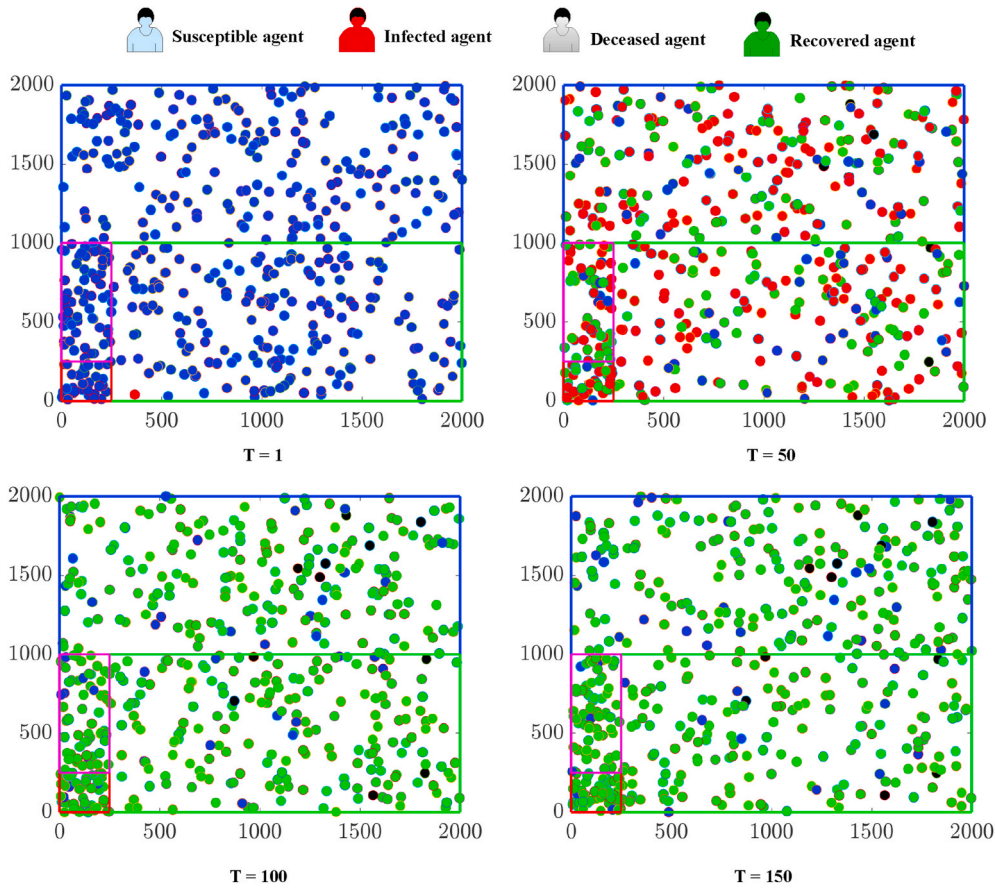


Fig. 18. Evolution of the multi-region scenario by iteration T , without social distancing policy.

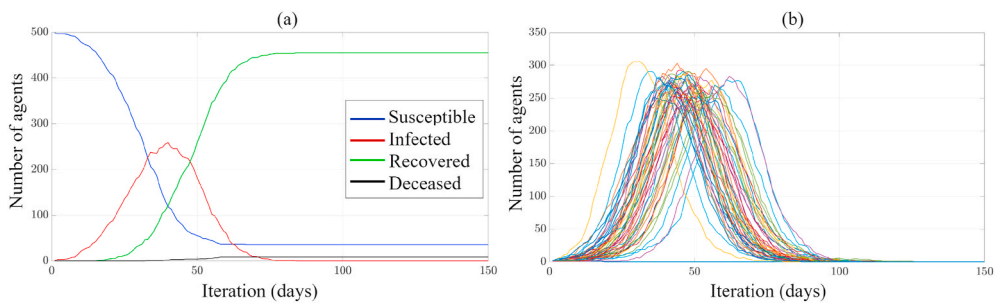


Fig. 19. (a) Typical response curve of the model in terms of the evolution of the number of susceptible, infected, deceased and recovered. (b) evolution curve of the number of infected by iteration of the 50 (fifty) processes of the model.

After choosing the next region of an agent, its (x, y) relative position within the new region is randomly defined (given that it needs to be in the designated region). Fig. 10 shows the application of the movement rule.

Each agent has its recovery time (T_{rec}) and mortality rate (γ) determined through Equations (2) and (3), respectively. From the moment a given agent n is infected, an algorithm computes the number of iterations in which the agent will be affected by the disease.

In each simulation iteration, this number is compared to the agent recovery time (T_{rec}). When they are equal, the algorithm generates the mortality probability of the agent, a random number MP . If MP is lower than (γ), the agent goes to the deceased state, otherwise it goes to the recovered state. Whenever an agent enters the deceased state, it will not comply with any rule anymore. On the other hand, a recovered agent continues to comply with the movement rule. Fig. 11 shows the application of the agent deceasing and recovering rule.

5. Experimental results

We validated our proposed model in two different scenarios, to show its applicability and sensitivity (precision of the susceptible, infected, recovered and deceased number of agents in the scenario). It is important to mention that the model sensitivity evaluation allows for the assessment of the model parameters and to plot the statistical results.

5.1. Experiment 1: hypothetical scenario with social distancing

The first experiment modeled a hypothetical scenario with 500 inhabitants. The parameters were configured as shown in Fig. 12 and Table 3. The professional activity and purchasing power distributions were extracted from Ref. [25]. We also used a hypothetical population age pyramid.

This scenario used the distribution of infection rates (β), agent

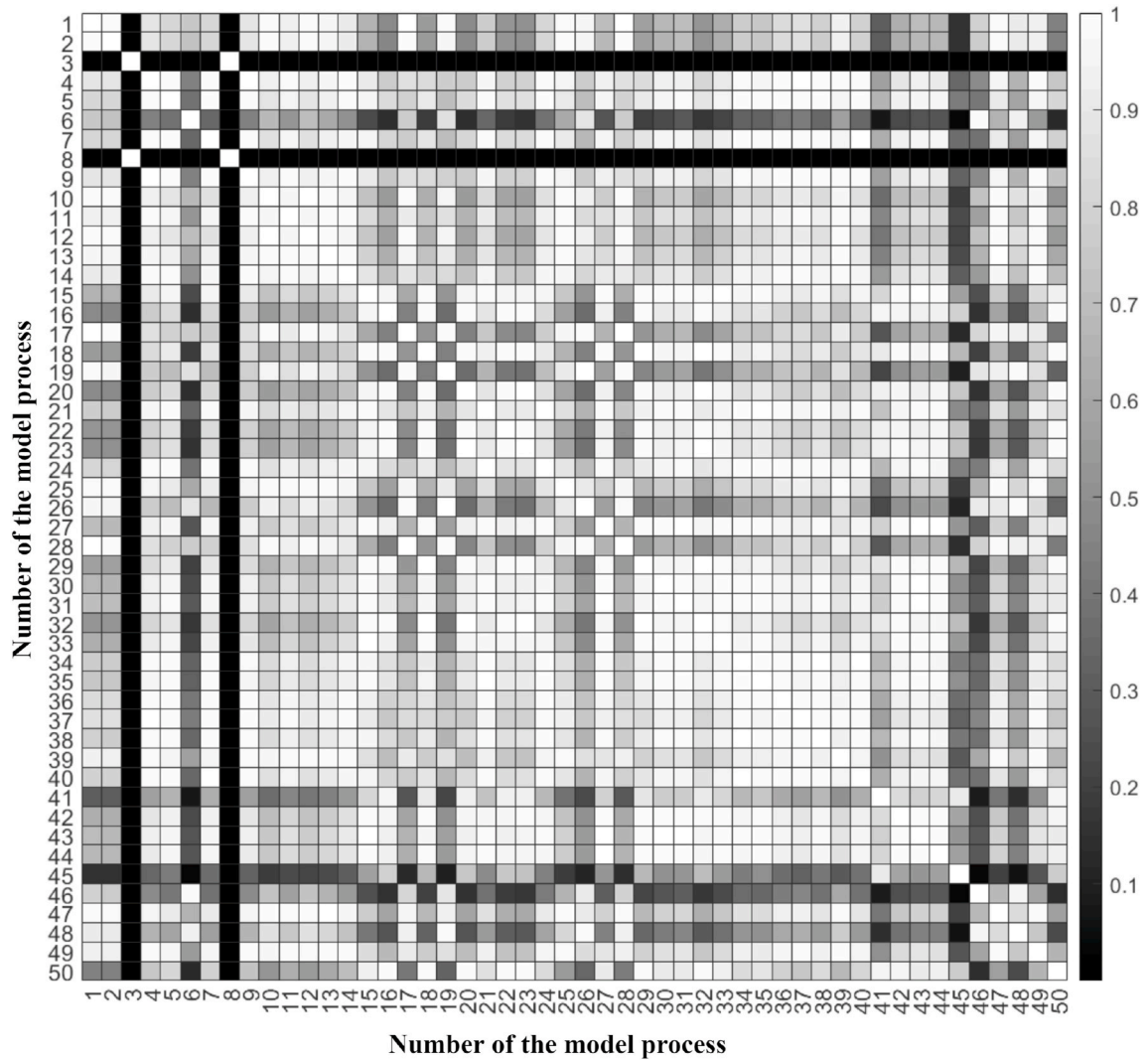


Fig. 20. Consistency/similarity evaluation matrix between the response curves of the number of infected of the model processes without social distancing.

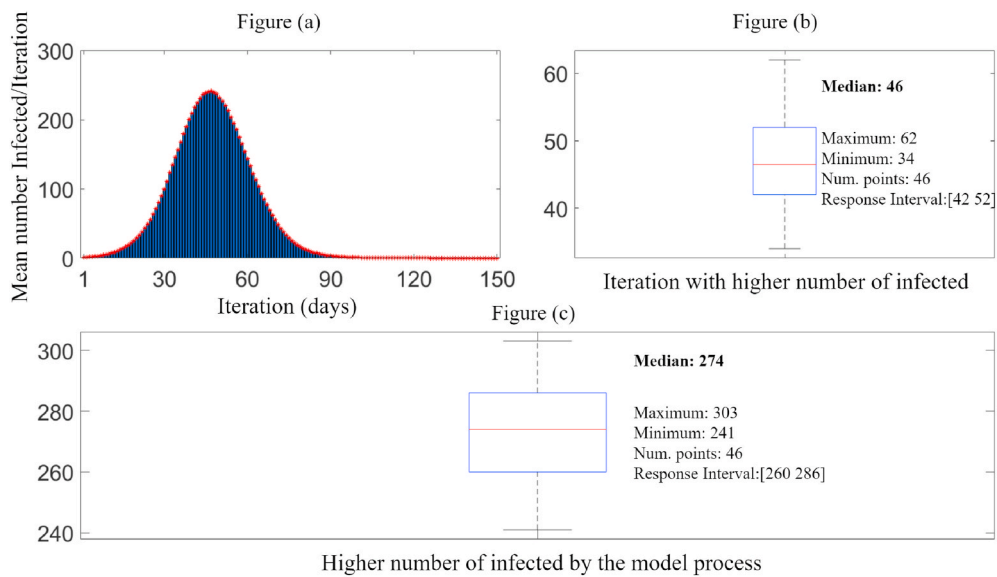


Fig. 21. (a) Graph with the iteration averages of the number of infected agents in the model. (b) Statistical analysis of iterations containing the peak of the response curves. (c) Statistical analysis of the maximum number of infected at the peak of the curves.

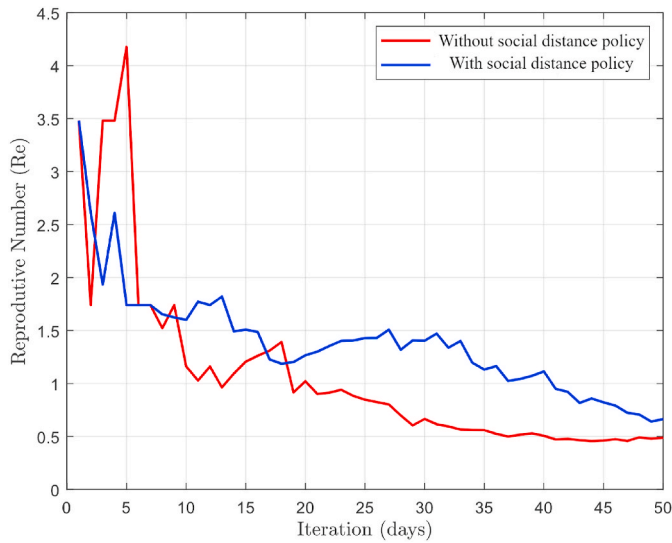


Fig. 22. Reproductive number curves for the model without (red) and with (blue) social distancing policy.

recovery time (T_{rec}), and mortality rate (γ) of agents, from Ref. [29]. The environment was modeled as a square with sides of 2000 points. The four environmental regions were defined as follows:

$X_{circulation} \in [0 \ 2000]$ and $Y_{circulation} \in [1000 \ 2000]$; $X_{home} \in [250 \ 2000]$ and $Y_{home} \in [0 \ 1000]$; $X_{school} \in [0 \ 250]$ e $Y_{school} \in [250 \ 1000]$; $X_{medical} \in [0 \ 250]$ and $Y_{medical} \in [0 \ 250]$.

The infection distance R was set to $R \leq 1$, and it was applied a social distancing policy. This scenario was processed 50 times to evaluate the model sensitivity and the relevance of the parameters. Fig. 13 presents the typical evolution of the scenario. Fig. 14 (a) presents a typical model response to the evolution of the numbers of susceptible, infected, deceased and recovered and Fig. 14 (B) the response curves of the number of infected per simulation run.

We performed an evaluation of the Shape Factor for the 50 response curves. This factor (Equation (6)) aims to evaluate the degree of consistency/similarity between two different response curves of the model. It varies from 0 to 1 (0 stands for no consistency/similarity, and; 1 stands for consistency/similarity of the answers). Observing Equation (6), we have the evaluation between the response curves of processes j and $j + 1$, being φ_j the vector that defines the infection curve of process j and t the transposed vector.

$$SF_{(j,j+1)} = \frac{|\varphi_j^t \cdot \varphi_{j+1}|^2}{(\varphi_j^t \cdot \varphi_j) \cdot (\varphi_{j+1}^t \cdot \varphi_{j+1})} \quad \text{therefore } j \in [1, 2, 3, \dots, 50] \quad (6)$$

Then, a matrix (Fig. 15) was elaborated to compare the results obtained, whose main diagonal has a unit value ($SF(j; j)$). This matrix aims to assist in the evaluation of the outliers processes regarding the response trend of the model.

The figure shows that executions 9,11,22,25,26,43,46,47 and 50 are characterized as outliers. Such outliers are characterized by the inability of the initial infected agent to infect any other agent due to its movements, thus promptly terminating the COVID-19 propagation. These executions reveal the influence of the infection distance parameter and of the environment size in the simulation.

Fig. 16 shows the sensitivity analysis of the executions, without the outliers. It shows that the curve ascendancy and descendant shape depends on the movement of infected agents. The recovery time also influences the descendant shape of the curve.

The analysis also allows us to evaluate the average number of infected agents per iteration, including the iteration in which the highest number of infected agents occurred (see Fig. 17). It shows that the peak

response occurred around iteration 75, with response interval between iterations 65 and 82. The highest number of coexisting infected agents was 142, with a response interval between 131 and 157 agents. The model predicts that, for this scenario with social isolation, there will be a probability of infection of the population around 13%–16% at the peak of the response curve.

5.2. Experiment 2: hypothetical scenario without social distancing

The second experiment did not consider social distancing policy. Thus, the movement rule was changed, as shown in Table 2. The changes increased the crowdedness of both home and industry, and workplace and school regions. This experiment used the same parameters as the first experiment. Fig. 18 presents a typical evolution of the scenario in the model without the application of social isolation. This scenario was also executed 50 times. Fig. 19 shows a typical evolution of the response of the number of susceptible, infected, deceased and recovered agents for this scenario.

This scenario presented only 4 outliers (executions 3, 6, 8 and 45 in Fig. 20). There were less outliers than experiment 1 due to the higher probability of movement and the non-decrease behavior of the infection rate β . In other words, without social distancing the COVID-19 epidemic does not cease prematurely.

The analysis also allows us to evaluate the average number of infected agents per iteration, including the iteration in which the highest number of infected agents occurred (see Fig. 21). It shows that the peak response occurred around iteration 46, with response interval between iterations 42 and 52. The highest number of coexisting infected agents was 274, with a response interval between 260 and 286 agents. The model predicts that, for the scenario without social isolation, the probability of population infection will be around 52%–57% at the peak of the response curve.

6. Discussion

The results presented in the two experiments reveal the potential of agent-based modeling to provide relevant information on COVID-19 pandemic prevention and coping strategies. This is reflected in the sensitivity analysis of the model responses both with and without social distancing policy.

The evolution in the number of susceptible, infected, deceased and recovered agents (Figs. 14 and 19) are similar to the responses of deterministic models such as SIR, SEIR and others based on differential equations ([7–10]). The results also did not present outliers between iterations 60 and 80, meaning that the results were consistent in the period of higher incidence of the pandemic spread.

The results show that social distancing policies leads to a longer period for the stabilization of the pandemic spread, when compared to the scenario without social distancing. The scenario with social distancing showed a more flattened, longer period curve than without social distancing.

It is also important to mention the role of the infection rate β , the recovery time T_{rec} , the size of the regions and the infection distance R in the model. These parameters allow the experiment designer model more accurately real-world scenarios of a given population.

Since the designer can model the population (agent parameters), the surrounding environment (environment model) and the infection parameters, it is possible to use the proposed model to aid decision-makers apply public policies. The simulation results can provide evidence for the effectiveness and the impacts of such policies (e.g. social distancing, closing schools and lockdown) in the social dynamic of the epidemic spread. For instance, a scenario of hospital overload and high shortage of healthcare resources can be tested - agents that are not healthcare workers will not be able to move to medical facilities. Social empathy actions (e.g. wearing masks), therapeutic actions or even vaccination can be modeled using the given parameters. These may lower the

infection rates or increase recovery time. Since the model provides the age parameter, the effects of vaccination scheduling can also be tested.

Another feature of the proposed model is the estimation of the reproductive number (R_e), which determines the potential for a virus to spread under certain conditions. If it is greater than 1, each infected individual is able to transmit the disease to at least one more individual, disseminating the virus. On the other hand, if it is less than 1, fewer individuals become infected and the infection recedes. This is a well-known concept in deterministic models such as SIR, SEIR and others based on differential equations. The proposed model tallies the infection rate for each agent and thus, R_e could be computed as the average infection rate for all agents in the pandemic period. Fig. 22 presents the reproductive number curve for both experiments ((a) and (b) without social distancing.

It can be noticed that with social distancing, the pandemic tends to be more enduring, but with much smaller amplitudes. The reproductive number R_e begins to show a value less than 1 (one) at iteration 40 for the model with social distancing and, at iteration 20 without.

7. Conclusion

The COVID-19 pandemic has challenged the scientific community to make efforts in the search for an adequate treatment for the cure. While this goal is not achieved, many governments have adopted measures to prevent and control the spread of the virus. Thus, mathematical and computational tools provide relevant information for social, political and economic decision-making that permeates the strategies to combat the pandemic.

In this paper, we have presented an agent-based model to analyze the spread processes of the COVID-19 epidemics in open regions. The proposed model incorporates aspects of social dynamics through simple rules based on statistical principles. From these models, a diversity of scenarios and hypotheses can be modeled to obtain the conditions of coexistence, habits and behaviors that need to be avoided and that corroborate the spread of the virus. We tested the proposed model in two different scenarios and our study indicates that two ways can help to suppress epidemics spread in: (1) acting on prevention techniques to reduce the infected possibility of individuals, and; (2) restricting infectious individuals enter the regions.

The model presented here is adaptable and flexible to the pandemic phenomenology, serving not only for the propagation modeling of COVID-19, but also as another tool for epidemiological modeling and decision making. Its use can bring benefits to society in terms of control of planned action, economy and employment of human resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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