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BMST 2024 : Complex System Modelling

The Link Between Public Health and Public Transportation: An Agent-Based Model Analysis

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Abstract

Agent-based modeling excels in analyzing the dynamics of complex systems, a method we leverage in our study using the DPSIR (Driver, Pressure, State, Impact, Response) framework to examine interactions between various agents intersecting together as a complex system. We utilize the GAMA platform to perform Agent-Based Modeling of disease transmission dynamics in Geneva, Switzerland, simulating the spread of a COVID-like disease. The focus is on assessing the impact on healthcare facilities and public transport systems to guide effective expansion and response strategies. The model integrates geographical data on healthcare centers and tram stops to build a digital twin of the Canton Geneva, using behavioral rules to simulate disease spread and response measures based on population interactions. Initial findings reveal that strategic public health interventions like the expansion of healthcare facilities and public transport stops have significantly improved access to healthcare, leading to a low infection rate and enhancing overall public health outcomes. This study offers valuable insights for policymakers to anticipate and mitigate the impacts of epidemic outbreaks in urban environments.

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Introduction

The global impact of the COVID-19 pandemic has highlighted the necessity for effective epidemic modeling to inform public health decisions and infrastructure development. Agent-based modeling (ABM) has historically been employed in the realm of public health, almost exclusively for modeling infectious disease transmission. ABMs are particularly suited for understanding dynamics of such complex systems because interactions between individuals, and individual interactions with local environments, drive patterns of disease incidence and persistence within populations, thereby capturing the complexities of disease spread in densely populated areas. While ABM research can provide valuable insights to public health policy, it also faces many challenges and limitations, including balancing simplicity with the complexity needed to accurately reflect real-world dynamics, and struggling with parameters setting due to a lack of representative empirical data. Validating ABMs is also difficult without sufficient independent data, limiting their effectiveness in simulating public health interventions and outcomes[4].

This report presents a comprehensive Agent-Based Model developed using the GAMA platform, designed to simulate the transmission dynamics of a COVID-like disease in Canton Geneva, Switzerland. Our model incorporates detailed geo-data of Canton Geneva, including the locations of hospitals and public transport facilities in Geneva, to analyze how the disease spreads among a certain number of population and to evaluate the potential impacts on critical urban infrastructure. Our study applies the DPSIR (Driver, Pressure, State, Impact, Response) framework [1] to structure complex systems and analyze how the evolution of disease transmission affects the number of infected individuals and travel times to hospitals, as well as how urban developments including public healthcare facilities and transportation systems evolve. Through this model, we examine a range of scenarios that include varying rates of disease transmission across different age groups and social interactions. We also assess how adaptive responses, such as enhancing healthcare capacity and adjusting public transportation systems, react to changing infection rates. An online repository provides full open access to the GAMA model code and all associated GIS files utilized in this model.

By providing a comprehensive understanding of how a COVID-like disease could spread in an urban context like Geneva, the report aims to equip stakeholders with the information needed to enhance preparedness and response strategies in the face of future epidemics.

1 Contextualization

1.1 Case study details

As the COVID-19 pandemic has affected millions worldwide, the demand for effective epidemic modeling to predict the spread of infectious diseases and inform public health decisions has become paramount. This case study employs such a model to simulate scenarios in a densely populated urban setting, focusing on the canton of Geneva. The model analyzes a group of individuals within the area, including both infected and healthy subjects. Individuals (people) move between their homes, hospitals, and social gatherings (friends' homes) using either walking or public transports (trams, trolleybuses and buses). Hospitals provide healthcare services to individuals, and Geneva Public Transport (French: Transports publics genevois, TPG) stops represent locations where people can access transport services. Information associated with healthcare centers and the TPG stops across the canton were incorporated. The distribution of the data is demonstrated in Figure 1.

(a) healthcare centers

(b) TPG stops

Figure 1: Distribution of healthcare centers and TPG stops of Geneva

1.2 Description of the DPSIR Framework

In the context of public health crises such as infectious disease outbreaks, understanding the dynamic interplay of various factors that contribute to the spread and management of disease is crucial. We developed a DPSIR model to explore how public health and transportation systems respond to and evolve with the transmission dynamics of a COVID-19-like disease. This model provides a structured approach for examining the complex interactions between human behavior, public health, transportation infrastructure, and disease dynamics, allowing for a comprehensive analysis of how these factors influence each other. This method helps in identifying effective strategies and responses to mitigate the spread of the disease and optimize health outcomes.

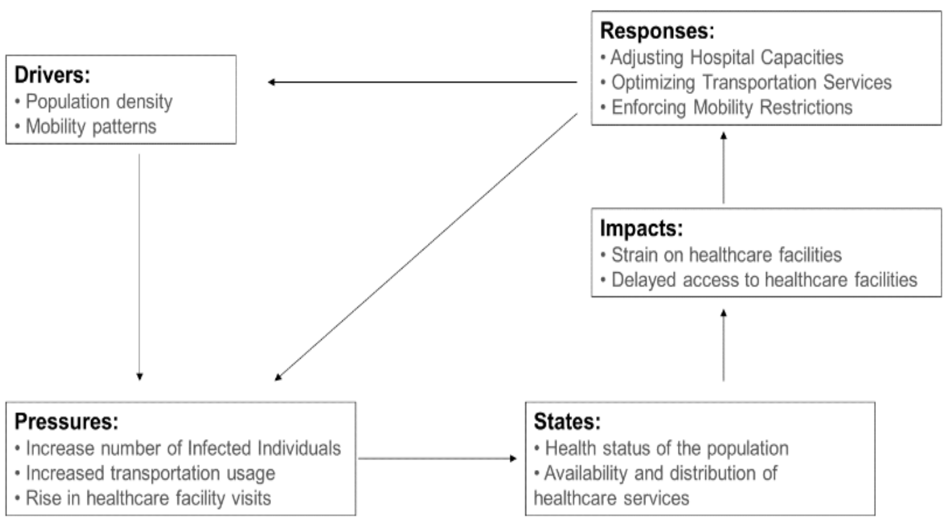


Figure 2: DPSIR Model Demonstrating Transmission Dynamics of a COVID-19-like Disease with a Focus on Healthcare Facilities and Public Transport

Below is a detailed description of the five elements within this DPSIR framework.

Drivers : In the scenario of disease transmission, the primary driving forces include population density and mobility patterns. High population density increases the likelihood of disease transmission due to closer and more frequent contact between individuals. Similarly, the mobility patterns of a population—how individuals move between different locations such as homes, workplaces, and social settings—play a critical role in the spread of diseases.

Pressures : These are the immediate conditions that arise from the driving forces and can exacerbate the situation. The number of infected individuals creates a direct pressure on the healthcare system, increasing the potential for further transmission. Additionally, increased use of transportation and higher visits to healthcare facilities can raise the risk of disease dissemination and strain on healthcare infrastructure, respectively.

State : This refers to the current condition of the system being analyzed, which in this case includes the health status of the population and the availability of healthcare services. The state reflects the community's resilience or vulnerability to outbreaks, shaped by factors like the distribution of healthcare resources and public health policies.

Impacts : These are the effects that pressures have on the state. For example, a surge in the number of infected individuals strains healthcare facilities, leading to delayed access to medical care and potentially worsening health outcomes. These impacts feed back into the system, influencing the state and potentially altering the driving forces and pressures.

Responses : In response to the identified impacts, strategies and measures are implemented to mitigate the adverse effects. In our model, we adjust hospital capacities to better accommodate the needs of the infected population, optimize transportation services to reduce contact rates, and enforce mobility restrictions to control the spread of the disease.

2 Description of the Agent-Based Model

This ABM acknowledges three types of agent species: people, hospital and tpg_stop. However, before getting a closer look on each agent species, we need to discuss the global section of this model.

2.1 Overview of the global section

```
global {
    file shape_file_hospitals <- file("../includes/soins.shp");
    file shape_tpg_stops <- file("../includes/tpg_stops.shp");

    float proba_cure <- 0.8;
    float cran <- 900.0;

    int people_sane <- 0 update: length(people where (each.state = "healthy"));
    int people_contaminated <- 0 update: length(people where (each.state = "infected"));
    int population <- 800 update: people_sane + people_contaminated;

    int time_to_go_to_hospital <- 0;
    int time_to_go_to_hospital_elder <- 0;
    int time_to_go_to_hospital_adult <- 0;

    int number_concerned <-0;
    int number_elder_concerned <- 0;
    int number_adult_concerned <- 0;

    list<string> line_cross_hospital <- nil;

    graph the_graph;
```

Figure 3: Global attributes of the model

This picture shows the global attributes utilized to describe the environment of the simulation. We can distinguish three types of global attributes. Those used to create the agents ('shape_file_hospitals' that contains the shapefile of the healthcare centers of Geneva, 'shape_tpg_stops' that has the value of the shapefile of the tpg stops, and 'population' which first value is the number of people agent created in cycle 0). Those utilized in several reflexes of some agents (such as'proba_cure'and 'cran'). And those that are used as data during the experiment (such as 'time_to_go_to_hospital', 'people_contaminated' or 'number_concerned' which is the number of people agents who got to a hospital agent since the beginning of the experiment). There is also the introduction of a graph and a list called 'line_cross_hospital' which will be described in the part focused on the hospital agent.

Additionally, the global section has three reflexes : ‘stop_simulation’ terminates the experiment when no “healthy” or “infected” people agents are present in the model. The two remaining reflexes will be detailed later on.
Finally, the global section has the ‘init’ to create the agents. This creation process will be explained throughout the species description.

2.2 Agent species

2.2.1 tpg_stop

```
species tpg_stop{
    rgb color;
    string line;
    list<hospital> hospital_near;
```

Figure 4: Attributes of tpg_stop agents

Tpg_stop agents represent the transport of Geneva. This agent aspect is a gray triangle whose shade depends on its ‘line’ attribute.
The last attribute of tpg_stop is the list ‘hospital_near’. It contains hospital agents whose distance from the stop does not exceed the ‘cran’ global attribute.
At cycle 0, the model creates tpg_stops from the shapefile “tpg_stops.shp”, which contains locations, name and line of each tpg stops. If two stops have the same name in the shapefile, only the first one created remains while the other one is deleted.
‘hospitals_near’ gets the value expected according to what we said above. If this list is not empty, the ‘line’ attribute of the agent is added to the global attribute ‘line_cross_hospital’ (if the line is not already a part of this list).
At cycle 0, the model sorts the tpg_stops with the tpg_stop reflex ‘sort_stops’. If the agent ‘line’ attribute is not in the list ‘line_cross_hospital’ or if no hospital agent is located under a distance of ‘cran’ (or least) : this agent dies. Otherwise, the agent gets a ‘color’ attribute according to its ‘line’ attribute.

```
else {int rg <- line_cross_hospital index_of self.line;
      color <- rgb(10*(1+rg),10*(1+rg),10*(1+rg));}
  }
```

Figure 5: Value of the ’color’ attribute after the reflex ’sort_stops’

2.2.2 hospital

```
species hospital {
    rgb color <- #green;
    point address;
    int capacity;
    list<people> patients <- nil;
    int number_people <- 0 update: length(patients);
```

Figure 6: Attributes of hospital agents

‘address’ is its location.

‘patients’ is a list of the people agents whose location is the address of the agent, the order of this list if the order of arrival of these people.

‘capacity’ is the maximum length of ‘patients’.

‘number_people’ is the length of ‘patients’.

At cycle 0, hospitals are created from the shapefile “soins.shp” and got a ‘capacity’ equals to 50. They are displayed as green triangle.
This agent species has a single reflex named ‘healing’ which occurs when the ‘patients’ list is not empty. In this case, each people agent from the list gots a probability to be healed (we will explain later what this means for the people agent). This probability is equal to the global attribute ‘proba_cure’.

2.2.3 people

Each person is represented by a ‘people’ agent in the model. During cycle 0, the number of people agents created is the value of the global attribute ‘population’.
It has many attributes, Most of them have to be described in order to understand

```
species people {
    point home;
    string category;
    string state;
    string target <- nil;
    people friend <- nil;
    int time_with_friend <- 3;
    float energy <- 100.0;
    float step;
    int time <- 0;
    string way <- "walk";
    float get_contaminate;
    float go_see_friend;
    float choose_tram;
    float cran_transport <-50.0;
    list<hospital> hopitaux_proches <- nil;
    list<point> add_hopitaux <- nil;
    list<tpg_stop> stop_near <- nil;
    list<tpg_stop> pathway<- nil;
```

```
if flip(0.73) {category <- "adult";
                get_contaminate <- 0.0013;
                go_see_friend <- 0.5;
                choose_tram <- 0.3;
                step <- 100.0;
                state <- "healthy";
                if flip(0.05){state <- "infected";} }
 else {category <- "elder";
                get_contaminate <- 0.016;
                go_see_friend <- 0.1;
                choose_tram <- 0.8;
                step <- 50.0;
                state <- "healthy";
                if flip(0.2){state <- "infected";}}
}
```

Figure 7: Attributes of people agents

the reflexes of the agent (the initial values of most of these attributes are available on the picture above).

'home' is its location at cycle 0.

'state' can be 'healthy' (if this is the case, the agent is displayed as a blue circle) or 'infected' (then the agent is displayed as a red circle).

'energy' is a percentage of living force.

'target' can have the value : 'hospital', 'friend' or 'nil'

'friend' gets the value of a people agent if 'target' is 'friend' (In the opposite case, it has the value 'nil')

'way' can have the value : 'walking' or 'transport'.

'step' is the ray of the circle in which the agent can move at each cycle, when 'way' is 'walking'.

'go_see_friend' is the probability to have 'target' equals 'friend' when 'target' is 'nil'

'choose_tram' is the probability to give the value 'transport' to the attribute 'way' when it is not already the case

‘get_contaminate’ is the probability to have ‘state’ equals ‘infected’ when the agent is near an infected people agent. (The initial value of this attribute regarding its ’category’ has been chosen according to data of the COVID 19 pandemic in Geneva)

‘time’ equals the cycle when the agent’s location is any hospital agent’s ‘address’ (or its location is equal to ‘friend”s ‘home’) minus the cycle when ‘target’ get the value ‘hospital’ (or ‘target’ get the value ‘friend’). (In fact, the obtention of this value is more complex and will be detailed in reflexes of people species)

cran_transport is the ray of the circle in which the agent can move is ‘cran_transport’ x ‘step’, when ’way’ is ’transport’.

‘hopitaux_proches’ (‘stop_near’) is the list of hospital agents (tpg_stop agents) reachable by the agent in a chosen area (the value of these attributes will be detailed below).

‘add_hopitaux’ is the address of each element in ‘hopitaux_proches’.

‘pathway’ is a list of tpg_stop agents. The construction of this list is developed in two reflexes of people agents.

‘category’ is its age field : it can be ‘adult’ or ‘elder’.

This category is chosen in the init section of the agent. According to the article [3], among the citizens older than 20 years old, 73% are aged between 20 and 59. Therefore, the ‘category’ of the agent has a probability of 73% to be ‘adult’. The value of the ‘category’ attribute has an impact on the value of several attributes such as : ‘go_see_friend’, ‘choose_tram’ or ‘get_contaminate’.

It can be noticed that the probability to have ‘state’ equals ‘infected’ in the initialization of the agent is higher than ‘get_contaminate’. We chose to do so in order to guarantee the presence of at least 3 infected people at cycle 0.

(Some attributes were not or partially detailed but their use will be outlined in the reflexes section)

2.3 Species' reflexes

2.3.1 People agents' reflexes

People agents have six reflexes.

Die When the 'energy' of the agent falls to 0.0%, it dies. Its presence is erased from the 'patients' list of every hospital agent and, if the 'friend' attribute of a people equals the agent, this attribute becomes itself.

Infection When the agent 'state' is 'infected', its 'energy' loses 0.1 unit. If the agent is not in a hospital, nor in a tpg_stop, the model creates the list of the people whose distance from the agent is at most 300.0 units. For each people agent in the list, it has a probability equals to its 'get_contaminated' attribute to become infected. If the agent is in a tpg_stop, only people agents in this tpg_stop are in the list.

End_play_time When the agent is at its 'friend''s home and the current cycle equals to 'time_with_friend', this attribute gets the value 3.'time' gets the value 0 and 'friend' becomes the agent.

Change_target This reflex is described by the tree diagram below. This reflex allows the agent to change its target, thus to change its future "action" in future cycles.

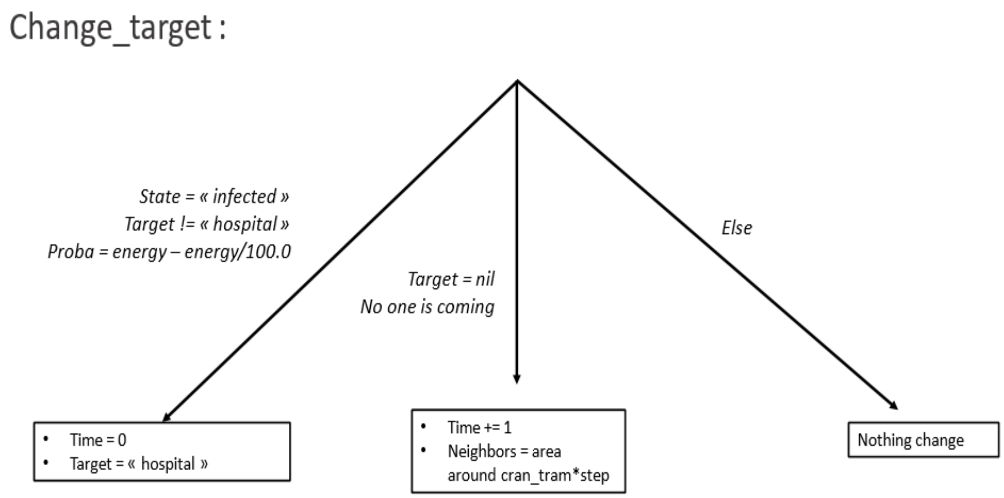


Figure 8: Tree diagram of the reflex 'change_target'

Go_hospital This reflex is also detailed by the tree diagram below.

The main idea is that when the agent acknowledges its infection (in the model, it means that the value of 'target' is 'hospital'), the model will make an estimation of the 'time' needed to get to the (nearest) hospital by 'walking'. If the value of this 'time' gets too high (and if there is a tpg_stop near the agent), there is a high probability for the agent's 'way' to get the value 'transport'. In that case, 'pathway' becomes the list of the tpg_stops the agent needs to reach to get to the hospital. When the agent reaches the last stop of this list, it has to wait until the 'number_patients' attribute is strictly lower than the 'capacity'.

(In the code, just after a value is affected to 'pathway', the element 'target_stop' is removed then added again to this list. This manipulation is an insurance that the last element of this list is indeed a tpg_stop whose 'hospital_near' attribute is not empty).

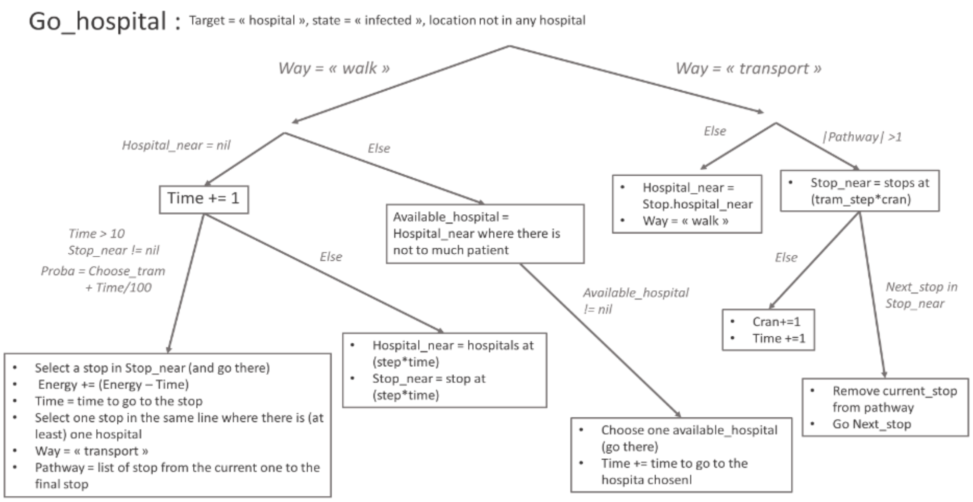


Figure 9: Tree diagram of the reflex 'Go_hospital'

Go_meet_friend This reflex is similar to the go_hospital reflex's pattern but the way to create the list 'pathway' is different.

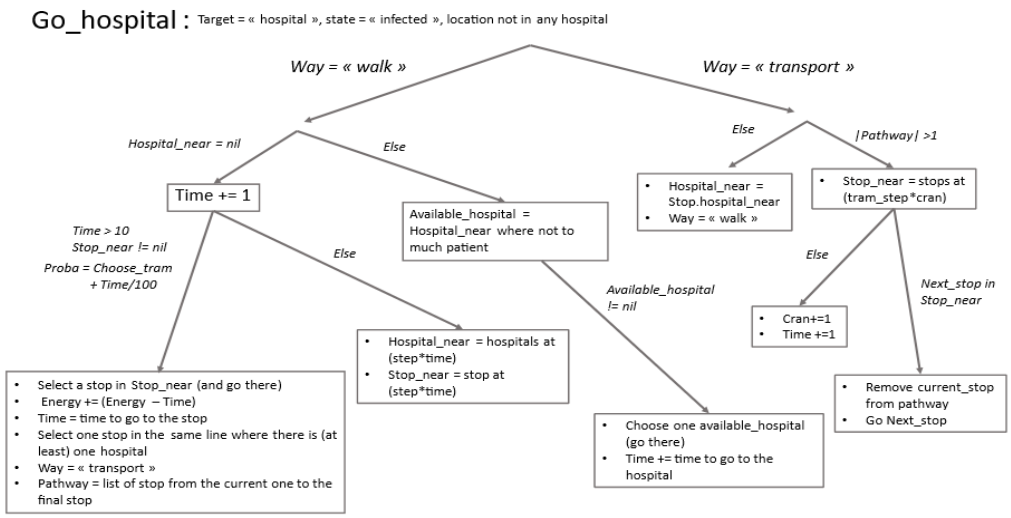


Figure 10: Tree diagram of the reflex 'go_meet_friend'

2.3.2 Hospital agents' reflex : 'healing'

For each people agent in the list 'patients', its 'energy' decreases by 0.1 unit. Then, its 'state' has a probability equal to the global attribute 'proba_cure' to become 'healthy'. If that is the case, its 'energy' goes back to 100.0%. Its 'target' becomes and its 'friend' becomes itself. Finally, to reproduce the concept of the immunity system, the 'get_contaminated' attribute is divided by 2. The 'patients' list of the hospital becomes the people agents of the previous list whose 'state' is still 'infected'.

2.3.3 Evolution of the environment

The evolution of the environment is programmed by a reflex called 'Environment_reaction'. This reflex is part of the global section. It is meant to propose responses of the environment regarding the state of the population (especially the portion of infected people agents). Among other measures, the tree diagram below shows that, if the percentage of infected people agents exceeds 75%, the value of 'go_see_friend' drops to 0.001, meaning that the probability for a people agent to "go see a friend" is nearly nil (thus the agent will stay at home). This phenomenon can be interpreted as a "lockdown". That is why the expression "lockdown measure" might be utilized to refer to this reaction of the environment.

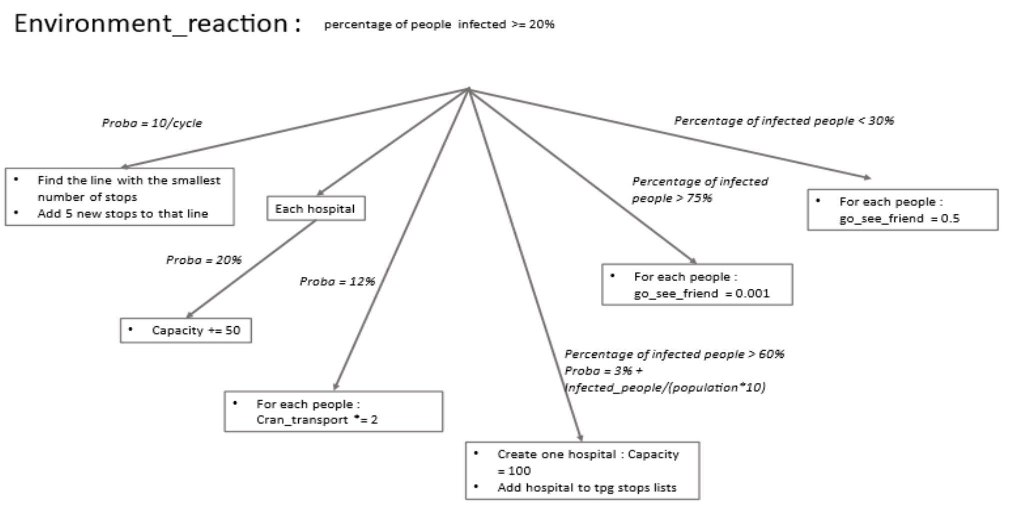


Figure 11: Tree Diagram for the reflex 'Environment_evolution'

2.4 Overview of the experiment section

```
experiment infection_tpg type: gui {

    parameter "Shapefile for the hospitals:" var: shape_file_hospitals category: "GIS" ;
    parameter "Probability to cure: " var: proba_cure min: 0.0 max: 1.0 category: "Hospital";
    parameter "Number of people: " var: population min: 200 max: 10000 category: "People";

    output {
        display city_display type:3d {
            species tpg_stop aspect: base ;
            species hospital aspect: base ;
            species people aspect: base ;
        }

        display population_information refresh: every(5#cycle){
            chart "Age_distribution" type: histogram background: #lightgray size: {0.5,0.5} position: {0, 0.5} {
                data "total_elder" value: length(people where (each.category = "elder")) color:#blue;
                data "elder_ill" value: length(people where (each.category = "elder" and each.state = "infected")) color:#blue;
                data "total_adult" value: length(people where (each.category = "adult")) color:#green;
                data "adult_ill" value: length(people where (each.category = "adult" and each.state = "infected")) color:#green;
                }
                 }

        monitor "time_to_go_to_hospital" value: time_to_go_to_hospital/(number_concerned+0.1);
        monitor "portion infected" value: people_contaminated/population;
        monitor "Population" value: population;
        monitor "number_hospitals" value: length(hospital);
        monitor "number_stops" value: length(tpg_stop);
        monitor "hospital_line" value: length(line_cross_hospital);
    }
}
```

Figure 12: Experiment section of the model

Aside from three parameters (as shown on the picture above), the experiment section is divided into three parts.
The first one is a 3D display to visualize the evolution of the agent during the simulation.
Then, one part allows the creation of an histogram to check the figures of the population (in four parts : total of adults, total of adults ill, total of elders, total of elders ill)
Lastly, the monitors helps to check the global state of the environment (all data provided by the monitors are registered in a text file entitled “res.txt”, the construction of the entire file will be detailed on the results chapter)

3 Results and discussion

3.1 Expected results

First of all, the experiment is expected to outline a drop in the number of people infected. Yet, in order to obtain successful results, we expect a healthy population at the end, without too many deaths during the simulation.
Moreover, by increasing the number of transport stops near hospitals and expanding the number of healthcare centers, we anticipate a dual benefit: a reduction in the proportion of the total population(regardless of age groups) that are infected over time and a decrease in the average time required for individuals to access healthcare services. The proximity of transport stops to healthcare facilities would likely enhance accessibility, allowing for quicker response times during health emergencies and more regular access to medical care for preventative measures and ongoing treatment. Furthermore, with more healthcare centers distributed throughout the area, healthcare resources would be less strained, enabling more efficient and effective care delivery. These enhancements in healthcare accessibility and response efficiency are expected to play a significant role in controlling the spread of the disease, ultimately leading to improved public health outcomes and a more resilient healthcare system.

3.2 Data collected in the model

To collect data during the experimentation, a reflex named 'saving_data' is added in the global section. This reflex creates a file named "res.txt" and writes several data in it at each cycle. This data are :

'Cycle' The current cycle

'Population' The population

'Portion_infected' The portion of infected people among the population

'Number_elder' The total number of people in the "elder" category

'percentage_elder_infected' The portion of elder infected in the total of infected people

'Number_adult' The total number of people in the “adult” category

'percentage_adult_infected' The portion of adult infected in the total of infected people

'average_time_to_go_hospital' The average number of cycle needed to get to the hospital

'average_time_to_go_hospital_elder' The average number of cycle needed to get to the hospital for an elder

'average_time_to_go_hospital_adult' The average number of cycle needed to get to the hospital for an adult

'number_hospitals' The number of hospitals created

'number_stops' The number of tpg_stops created

3.3 Results of the experimentation

```python
import matplotlib.pyplot as plt

with open("C:/Users/farat/OneDrive/Documents/Université/S6/projet/GAMA/GAMA_1.9.2_Windows/workspace/BMST/models/res.txt", 'r') as file:
    lines = file.readlines()

number_list = ["0","1","2","3","4","5","6","7","8","9","."]
results = []

for line in lines:
    numbers_cycle = [""]
    for e in line:
        if (e in number_list):
            numbers_cycle[len(numbers_cycle) -1] = numbers_cycle[len(numbers_cycle) -1] + e
        else:
            if (numbers_cycle[len(numbers_cycle) - 1] != ""):
                numbers_cycle[len(numbers_cycle) - 1] = float(numbers_cycle[len(numbers_cycle) - 1])
            else:
                numbers_cycle.pop(len(numbers_cycle) - 1)
            numbers_cycle.append("")
    numbers_cycle.pop(len(numbers_cycle) - 1)
    results.append(numbers_cycle)
```

```python
cycle = []
population = []
portion_infected = []
number_elder = []
number_elder_infected = []
portion_elder_infected = []
number_adult = []
number_adult_infected = []
portion_adult_infected = []
average_time_to_go_to_the_hospital = []
average_time_elder = []
average_time_adult = []
number_hospitals = []
number_stops = []
```

```python
for r in results:
    cycle.append(int(r[0]))
    population.append(r[1])
    portion_infected.append(r[2])
    number_elder.append(r[3])
    number_elder_infected.append(r[4])
    portion_elder_infected.append(r[5])
    number_adult.append(r[6])
    number_adult_infected.append(r[7])
    portion_adult_infected.append(r[8])
    average_time_to_go_to_the_hospital.append(r[9])
    average_time_elder.append(r[10])
    average_time_adult.append(r[11])
    number_hospitals.append(r[12])
    number_stops.append(r[13])
```

Figure 13: Python code to analyze the file "res.txt"

The graphs provided in this part display the results of an experimentation of 6842 cycles. As shown by the results, this experimentation ended because no infected people remained in the simulation (triggering the global reflex ‘stop_simulation’). The data provided by the document “res.txt” had been exploited by Pyhton in order to get the graphs needed.

Population

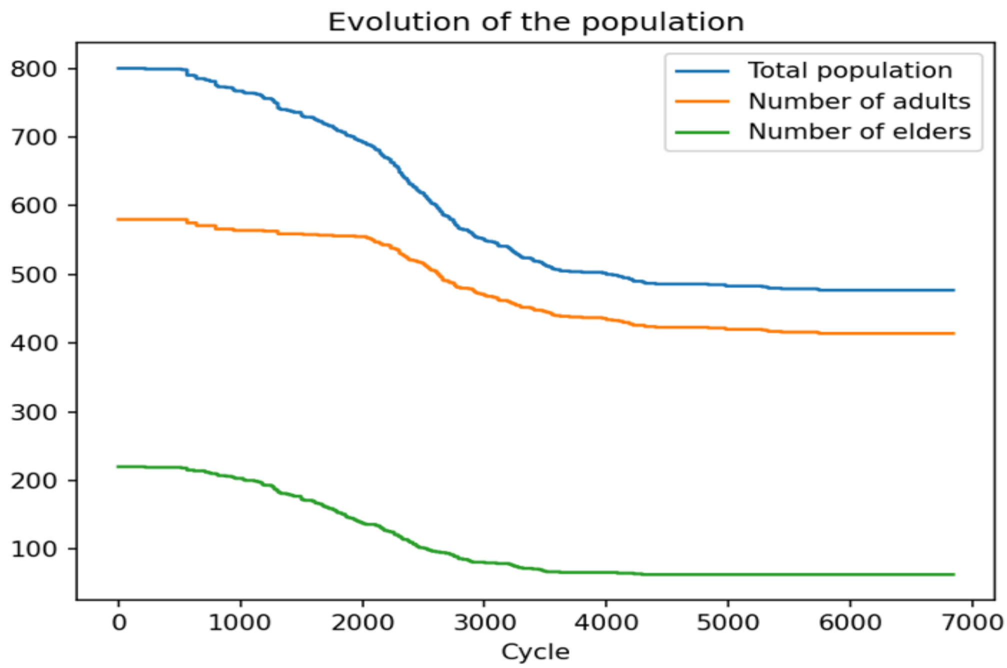


Figure 14: Evolution in the Population over cycles

The population is unchanged for nearly 500 cycles before decreasing significantly until the cycle 4200. After this cycle, the population slightly decreased but is mostly stable until the end of the experimentation. We can see that 300 "people" agents died during the experimentation.

If we focus on adult agents in the category "adult", their number slowly decreases between cycle 500 and 2000 (around 20 "adults" died), then it drastically decreases until cycle 4200. Then, like the total population, the number of "adults" is stable, 165 "adults" died during the experimentation.

The number of "elders" follows the same pattern that the total population except it goes from 220 to 68. Thus nearly the same number of "adult" and "elder" die in this experiment. However the portions are drastically different since 70% of elders die while 25% of adults die.

Infected agents

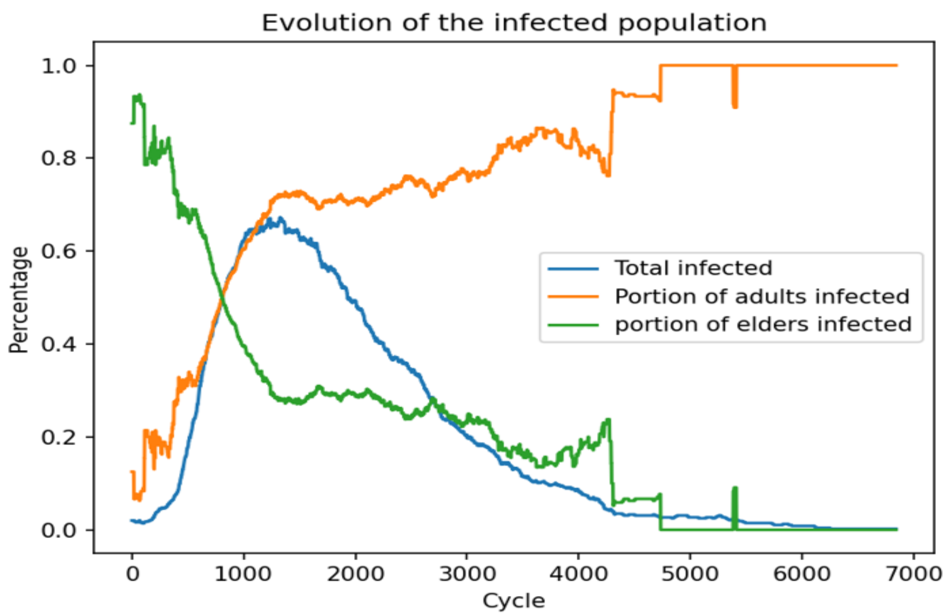
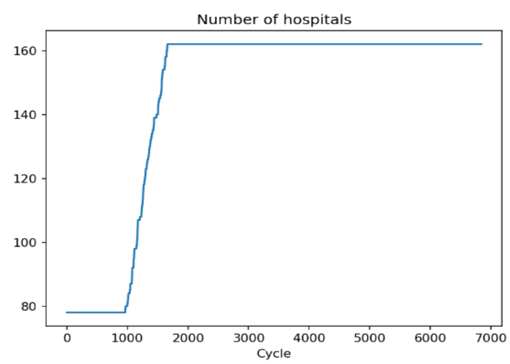


Figure 15: Evolution in the population infected over cycles

We can notice that the percentage of infected individuals drastically escalates at the beginning of the simulation, reaching a peak of 67% around the 1500th cycle. Afterwards, the figures sharply drop until the cycle 4200, then steadily decline until the simulation concludes. We hypothesize that at the beginning of the outbreak, the increased use of public transportation to access healthcare contributed to higher infection rates and placed additional strain on hospital capacities. Regarding the data of the portion of adults and elders infected, the simulation outcomes deviate from the anticipated results. Initially, the elders represent a larger fraction of the infected population compared to adults. However, this trend quickly reverses, with adults becoming the majority of infected people from cycle 1000 until the end of the simulation. These unexpected results could be explained with the great amount of elders dead during the simulation. On the other hand, people agents with the “adult” category have a higher probability to choose to meet a friend, thus the number of infected adults increases.
The previous graph underlined a sharp decrease in the population (caused by the

death of infected people agents) which could obstruct the increase of the portion of infected people, or even slightly decrease this percentage. Though it could hardly explain this drastic fall in the figures by itself. Consequently, this line testifies of the presence of other factors that could have reduced the number of infected people. This observation can be confirmed since the percentage of infected people is higher than 20% between the 700th cycle and the 3000th cycle, so the global reflex 'environment_reaction' is activated during these cycles. With that in mind, we can make the hypothesis that the responses of the environment significantly improve public health in more or less 800 cycles (since the peak is reached at the cycle 1500). Moreover, the percentage of people infected is never higher than 68% during the simulation, thus the "lockdown measure" has not been activated. So other measures had been effective to curb the infection.

Hospitals and tpg stops



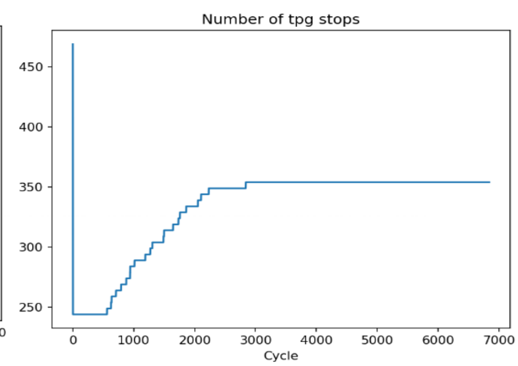


Figure 16: Evolution of the number of hospitals and tpg stops over cycles

The number of hospitals is unchanged for 1000 cycles. After this, the number skyrockets from 74 to 162 in nearly 800 cycles. The previous results highlighted that more than 20% of the population was infected between these cycles. After the cycle 1800, the number of hospitals stayed 162. We can conclude that the infection is partially curbed by the creation of new hospitals.
When it comes to the number of tpg_stop, this is a similar observation. Firstly, this number is stable until the 600th cycle, then it increases to reach the value of

354 tpg_stops at the cycle 3000. Then it remains the same until the end of the simulation. This increase of tpg_stops induces better access to healthcare centers. Therefore, we should witness a decrease in the average time needed for an agent to reach a hospital.
Our initial findings suggest that a rapid increase in the number of healthcare centers and stops leading to these healthcare centers can lead to a reduced infection rate. While this might seem unrealistic, the conversion of large-scale public venues into makeshift hospitals was a widely adopted strategy in many countries like China, USA, UK, Spain during the onset of the COVID-19 pandemic. This approach helped countries and regions maintain the operational integrity of their healthcare systems during the crisis[2].

Average time to access a hospital

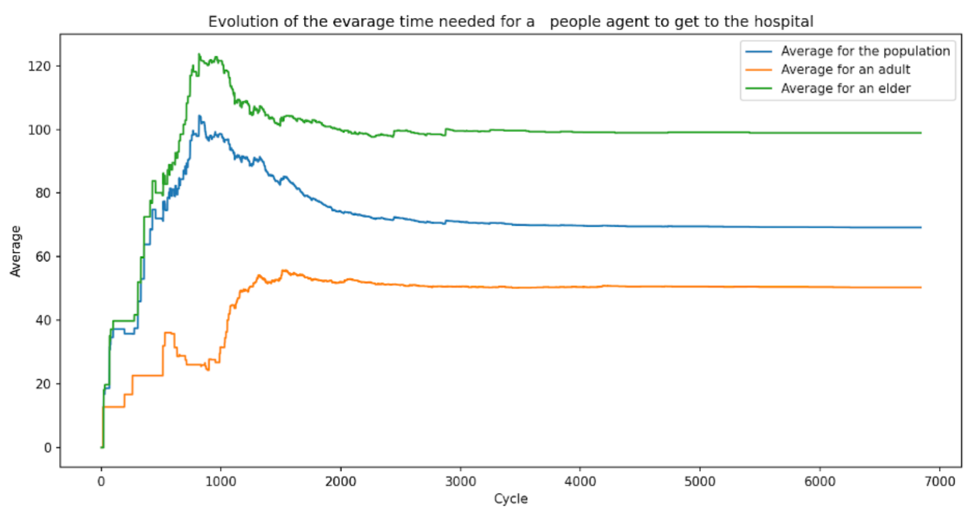


Figure 17: Evolution of the average time to go to the hospital over cycles

We observe a sharp increase in the average time it takes for people to reach the hospital, peaking at around the 1000th cycle. This initial spike is likely due to a surge in infections early in the simulation, which causes traffic congestion and extends travel times to hospitals. However, as expected from the previous observations, the average decreases until the cycle 3200, likely because of the

increased number of tpg stops and hospitals, which improves accessibility and reduces congestion. Afterwards, the average is very slightly decreasing around the value of 110 cycles.
The average time needed for an adult to get to the hospital follows the same pattern that the global average of the population but with lower values. At the end of the simulation, this average is 70.
For the elders, this average does not follow the same pattern. Instead, this value greatly increases during 2000 cycles then remains stable around 55 cycles until the end of the experiment.
While, there is no improvement in the average time to get to a hospital for elders, this average remains lower than the adults' average. This phenomenon could be explained by the fact that elders quickly choose to use transport (their probability 'Choose_tram' is higher than the adults' probability) and do not go out often to meet a friend (thus they have less chances to get infected). A second theory could be that, since the number of elders drastically decreases during the experimentation, this average can not evolve significantly enough to get higher than the adults' average.

3.4 Discussion

The results show that our model works well. Specifically, it reduces the portion of the infected population and decreases the time required to access healthcare centers over time, which can be attributed to the increased number of healthcare facilities and transport stops.

However, the model exhibits several limitations.
Firstly, the experimentation hardly works with a population higher than 1000 because there are too many agents to operate. There is also a limitation in the data collected. Indeed we should have monitored other possible factors that could have curbed the infection, such as 'cran_transport'or the 'Capacity' attribute of hospital agent.
Furthermore, the filter of tpg_stop at the cycle 0 reduces the number of distinct spaces in the model. Meaning the people agents are more likely to cross each other several times. As a consequence, this filter allows more infected people agents to meet with healthy agents in stops.

Additionally to these limitations, our model has a few weaknesses.
It does not utilize actual demographic data from the region. It starts with a fixed population size and does not account for demographic changes such as births over time. To add complexity, we categorize the population into two age groups. This approach has yielded interesting insights, such as varying infection rates between these groups over time. Yet, limiting the simulation to just two age groups does not fully capture the complex nuances of real-world demographics. Also, our model simulates social interactions, such as visiting friends, to mimic real-world behavior. However, these agents' behaviors and interactions are overly simplistic and uniform, which could undermine the complexity and accuracy of the simulation's outcomes.
This simplistic modeling is also outlined by the conception of hospital agents. All of them have the same initial "capacity" value and they have hardly any specific characteristic aside from the localisation. The same point applies to the tpg_stop agents. They do not have a direction nor a capacity of people agents.
Moreover, the estimation of the 'time' to go to the hospital is not actually the number of cycles the agent spent before entering the hospital. Thus the number of cycles spent being infected is also higher, which can explain the amount of death at the beginning of the simulation (also the calculus of energy when the infected individually switches from "walking" to "transport" is quite rare and should be changed).
Finally, some reactions of the environment should be upgraded. For instance, as soon as the rate of infected people agents is between 20% and 30% the probability to go see a friend becomes the same for everyone (and is very high : 50%). This choice nullifies the intended distinction between the probability of adults and the elders' one.

On the other hand, this ABM shows promising results and has many strengths. First of all, our model utilizes geodata from healthcare centers and public transport stops to construct a digital twin of the Canton of Geneva. We also selected attributes based on the COVID-19 pandemic data from Geneva to simulate a similar disease transmission.
Moreover, though the environment might lack realism, the evolution of people agents in this environment shows a great amount of complexity. For instance, the fact that infected people agents do not acknowledge their infection (meaning their target is not simultaneously "hospital" just after being infected) is quite realistic and allows a propagation of the infection. Also, the idea "lockdown measure" as a last resort to curb the infection is adequate with the inspiration from the COVID 19 pandemic.

Conclusion

In this report, we developed a DPSIR model and adapted it into an ABM to investigate the transmission dynamics of a COVID-19-like disease, with a specific focus on the implications for healthcare facilities and public transport expansion. This simulation reveals that strategic expansions in healthcare facilities and public transport accessibility directly contribute to lowering infection rates and improving public health outcomes. These findings support and reflect the efficacy of similar policy decisions made globally during the COVID-19 pandemic. By demonstrating the critical role of strategic healthcare planning and infrastructure adjustments in managing epidemic outbreaks, this study underscores the value of agent-based modeling as a powerful tool for informing and enhancing health policy decisions in urban environments during crisis situations.

Future work

Improvements to our model should address the previously discussed limitations. To more accurately simulate human behavior in response to an epidemic, we should incorporate realistic decision-making processes based on symptoms and agent characteristics. For instance, younger individuals with mild symptoms might opt to recuperate at home, whereas older individuals may be more inclined to seek hospital care. Including preventative measures such as social distancing and mask-wearing could also enhance the realism of the agents' responses, leading to more accurate modeling of movement patterns and adherence to health guidelines.Utilizing real demographic data from the Canton of Geneva would provide a more authentic evolution of the population. Expanding the simulation to include a broader range of age groups, socioeconomic statuses, and actual health conditions would better reflect the diversity of the population. For instance, wealthier families might choose to travel to hospitals in private cars to avoid exposure to public transportation, which introduces the need to consider factors like parking availability near healthcare facilities. Also, buildings and activities should be more diversified. For instance, the notion of "going to work" and the needed buildings could be added.
To further enhance the model's realism, we consider incorporating various stages of infection and recovery, as well as vaccination strategies at later stages. This would enable a more detailed representation of disease progression and transmission dynamics, offering deeper insights into potential epidemic responses and outcomes.
Regarding tpg stops, we could try to keep each one of them from the shapefile in order to create a more complex network. More precisely, this decision could increase the number of separated areas but also complexify the choice of people agents to take transportation. Indeed, not only tpg stops in lines crossing an hospital would be in the model, every tpg stops would, so the agent might have to get out at a stop to take an other line.

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