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# Applying geospatial multi-agent system to model various aspects of tuberculosis transmission

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ABSTRACT

*Introduction:* The paper presents epidemiological process modeling, with a focus on tuberculosis utilizing multi-agent system.
*Material and methods:* This study involves the development of an algorithm that harnesses the potential of artificial intelligence to create a geospatial model that highlights the different pathways of TB transmission. The modeling process itself is characterized by a series of key stages, including initialization of the city, calibration of health parameters, simulation of the working day, propagation of the spread of infection, the evolution of disease trajectories, rigorous statistical calculations and transition to the following day. A comprehensive description of the course of active tuberculosis is presented, following the official hypothesis recommended by the World Health Organization. A comprehensive simulation, illustrating the propagation of tuberculosis in an entirely healthy environment devoid of any preventive or therapeutic measures, is presented. To ascertain the adequacy of the model and its sensitivity to the principal parameters governing the course of tuberculosis, a series of experiments were meticulously conducted, employing three distinct approximations, namely: the basic model, the model incorporating mortality factors, and the comprehensive model, encompassing all relevant aspects.
*Conclusions:* The model's results exhibit stability and lack of significant fluctuations. The statistical values obtained for infected, latent, and recovered individuals align well with known medical data, confirming the model's adequacy.

The proposed model allows for tracking and analyzing the life and behavior of each individual agent, enabling a thorough assessment of tuberculosis infection spread and the development of prevention strategies.

## 1. Introduction

Forecasting epidemiological processes holds immense importance as it allows for understanding and anticipating future disease and epidemic trends. Harnessing the potential of artificial intelligence (AI) and multi-agent systems is proving crucial, as these advanced tools allow vast amounts of data to be processed and systems simulated.

By examining a wide range of parameters, these methods quickly identify intricate relationships between different factors, paving the way for accurate predictions of the epidemic's future trajectory. For instance, AI can analyze tuberculosis incidence data across different global regions and combine it with information on other diseases that cause concurrent comorbidity, which has a significant impact on the human immune system. This analysis can uncover latent interdependencies, allowing informed predictions to be made about the future course of the epidemic.

Moreover, the potential of AI goes beyond simply modeling epidemiological processes; it also holds promise for testing different treatment and prevention strategies. By using multi-agent modeling in conjunction with reinforcement learning neural networks, it is possible to identify the most effective preventive measures against the spread of tuberculosis in specific regions.

Thus, artificial intelligence can be a very useful tool in predicting epidemiological processes and performing various tasks in the healthcare domain. However, it is worth noting that artificial intelligence is no

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substitute for professional, personalized human experience and expertise, so it should be used with understanding and careful consideration.

The development of a reliable analytical model holds immense potential to be highly beneficial in practical healthcare, particularly in formulating strategies to combat tuberculosis transmission within the countries of the WHO European Region, that experience significant migration from high-risk tuberculosis regions [1,14].

The primary objective of this research is to devise an algorithm that utilizes the power of AI and neural networks to build a geospatial model of tuberculosis transmission scenarios.

The study was conducted during the period spanning October 2022 to April 2023 [2].

## 2. Material and methods

The primary aim of this study was to develop a model that accurately simulates the transmission of tuberculosis within an urban setting. To achieve this objective, the researchers employed the GeoCity model (v1), capable of highly realistic depiction of the city's dynamics on an hourly basis. The formalized model is represented as Equation (1) [3,5]:

$$\boldsymbol{GeoCity} = \{\boldsymbol{G}, \boldsymbol{T}, \boldsymbol{A}, \boldsymbol{R}, \boldsymbol{H}, V\}_{city}., \tag{1}$$

where $\boldsymbol{G}$ represents the set of geo-objects constituting the city, encompassing elements such as the, $\boldsymbol{T}$ denotes the transport utilized by agents during the simulation, incorporating both public transport and private cars. Additionally, it considers individuals who travel on foot without any transportation, $\boldsymbol{A}$ - a list of agents residing in the city, each characterized by specific attributes, including age, gender, workplace, residence, and more, which collectively define their daily schedule. This schedule contains a list of locations where the agent is present during specific hourly intervals. $\boldsymbol{H}$ accounts for the health attributes of each agent, with attributes tailored to the specific infection being modeled, $\boldsymbol{V}$ encompasses the rules governing the transmission of infection, dictating how the disease spreads from infected individuals to healthy ones, and defining the progression of the disease.

The process of initializing the model parameters and simulating the daily schedule is comprehensively detailed in (v1). Fig. 1 visually illustrates the procedure involved in modeling the transmission of infection.

The spread of tuberculosis is characterized by an average of 44 active human tuberculosis cases per 100,000 population [4]. Hence, to achieve adequate modeling, such systems should ideally have at least 100,000 agents. However, this can give rise to two challenges.

It is worth noting that despite tuberculosis being transmitted through the airborne route, its progression differs significantly from other respiratory infections like influenza or COVID-19, both in terms of duration and nature. Fig. 2 illustrates the course of active tuberculosis, adhering to the official hypothesis recommended by the World Health Organization [19,23].

As depicted in Fig. 2, when a healthy person (***S*** - susceptible) comes into contact with an infected individual (***I*** - infected), there is a certain probability of becoming infected. Unlike viruses, 90 % of those who become infected enter a latent state (***L*** - latent). In this state, they carry the bacteria but remain asymptomatic, do not spread the infection, and can coexist with infected individuals without transmitting the disease [15,17]. The remaining 10 % progress to an active state of infection (***I*** - infected), where they exhibit symptoms and can spread the disease to others [22]. It is important to highlight that tuberculosis has a relatively high mortality rate of 10.4 % [16]. Consequently, after contracting the disease, a portion of individuals experience fatalities (***D*** - death), while others recover (***R*** - recovered), which is analogous to the latent state. In other words, those who recover remain carriers of the bacterial infection throughout their lives but do not transmit the infection to others [13,20,

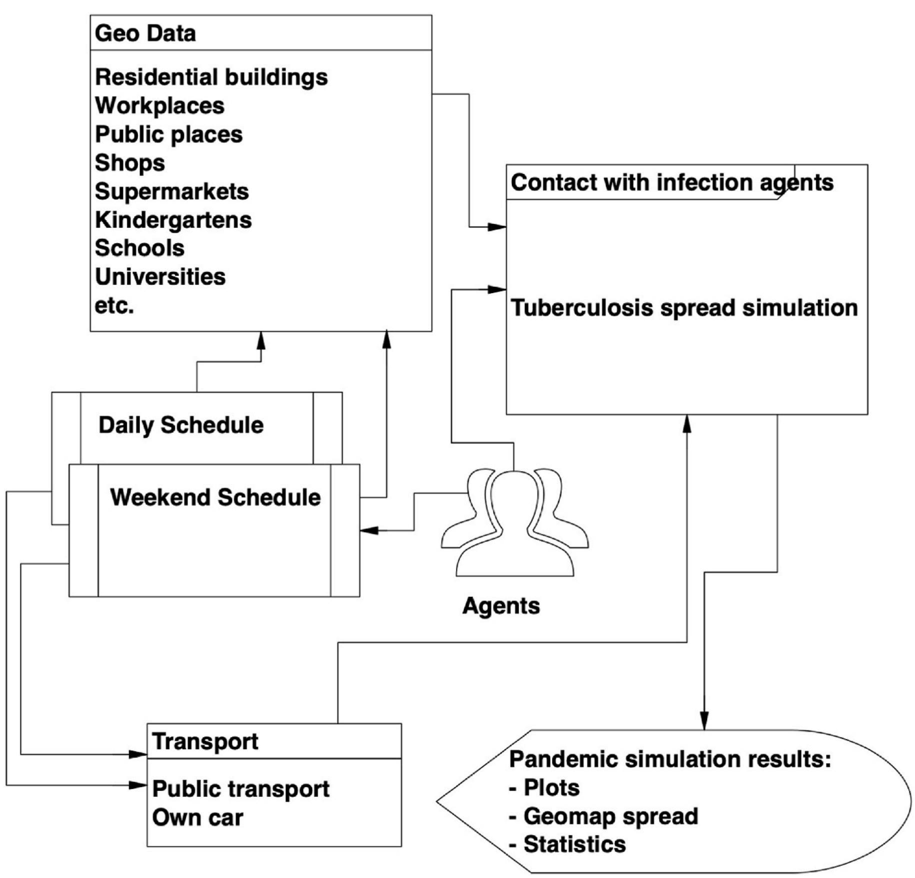


**Fig. 1.** Demonstrates the formalization of the GeoCity model's functioning, using a pandemic scenario as an illustrative example.

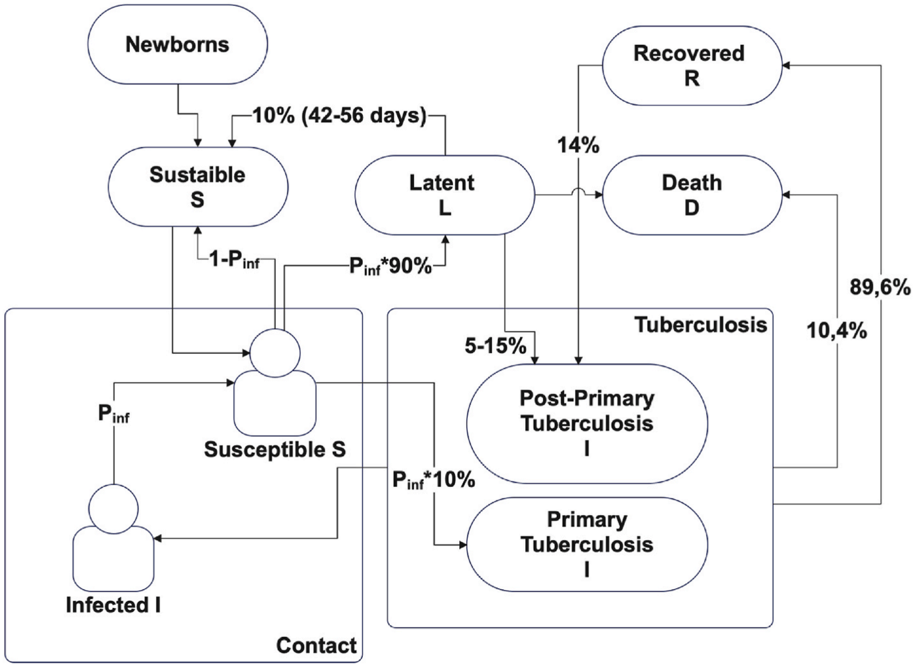


**Fig. 2.** The course of tuberculosis in case of human infection according to World Health Organization.
Note. Feshchenko Yu.I. et al., 2018.

21].

### 2.1. Model parameters structuring [3]

In summary, the attributes and functional dependencies can be categorized into three groups: static or deterministic attributes determined by known statistical data or clear formulas, stochastic attributes and functions containing stochastic parameters determined randomly, empirical parameters determined by fitting computer simulation results to real data (Table 1).

As observed in Table 1, the majority of attributes and functional dependencies, such as rules for state changes and probability of infection, can be accurately defined based on available tuberculosis statistics. Similarly, stochastic attributes and their corresponding state change rules are also well-defined, relying on medical research. The key distinction is that processes like infection, recovery, and death are probabilistic and are simulated using a random number generator.

Empirical parameters in the model include the infection rate (***IR***), which can be determined by comparing the model's infection rate with real data.

Another set of empirical parameters are attributes $\boldsymbol{a}$ and $\boldsymbol{b}$ used in the function for determining infectivity. These parameters and the function's adequacy can be established by comparing the actual infectivity dynamics of TB patients with the function's results. Given the well-studied nature of tuberculosis, identifying these values and evaluating their accuracy is a manageable task, as discussed in the next section.

The contagiousness function provides a continuous value of the contagion level that never reaches exactly 0. To determine the threshold for recovery α, a value is chosen such that the patient's contagiousness remains small enough for the number of sick days to equal the average duration of tuberculosis treatment $(\boldsymbol{con}(\boldsymbol{t_{dur}}) \leq \boldsymbol{\alpha})$, *where* $\boldsymbol{t_{dur}}$ – is the average duration of tuberculosis treatment.

**Table 1**
Classification of model attributes.

| Object | Static, deterministic | Stochastic | Empirical |
|---|---|---|---|
| Healthy data | $\boldsymbol{st}, \boldsymbol{t_{st}}, \boldsymbol{P_{pt}}, \boldsymbol{P_{death}}, \boldsymbol{P_{bel}}, \boldsymbol{P_{pp}}, \boldsymbol{P_{rec}}$ $\boldsymbol{d_{min}}, \boldsymbol{d_{max}}$, **md** | $\boldsymbol{bel}, \boldsymbol{t_{bel}}, \boldsymbol{pp}, \boldsymbol{t_{pp}}$, | |
| Rules of viruses spread | $\boldsymbol{P_{inf}}$, $\boldsymbol{St_{L/S}}, \boldsymbol{St_{L/I}}, \boldsymbol{St_{R/I}}$ | $\boldsymbol{St_{inf}}, \boldsymbol{St_{R(D)}}$ | **IR** ***con***, **a, b,** $\boldsymbol{\alpha}$ |

Note. Results of simulations.

## 3. Results and discussion

### 3.1. Parameters of the GeoCity city model

Lviv, the largest regional center in Western Ukraine, was selected as the test city for modeling tuberculosis spread. The city's population is approximately 720 thousand [2]. To align the statistics with a scale of 100,000 people, the multi-agent system will consist of this number of agents. As the city's population is about 7.2 times larger than the number of agents in the model, all city parameters (except for area and distances) will be proportionally reduced.

Table 2 presents a comparative analysis of real geographical features of the city and their corresponding model parameters. According to statistics [2], only 25 % of Ukrainians own a car, indicating that 75 % of the population use public transportation or are pedestrians. In our simulation, 50 % of agents will use public transportation, while 25 % will be pedestrians.

**Table 2**
Geodata and population data comparison for Lviv city.

| | Lviv | Model |
|---|---|---|
| Population ($\boldsymbol{P}$) | ~720,000 | 100,000 |
| Workplaces ($N_w$) | 33000 | 5000 |
| Houses ($N_h$) | 244727 | 33333 |
| Kindergartens | 115 | 15 |
| Schools | 155 | 22 |
| Universities | 29 | 4 |
| Hospitals | 7 | 1 |
| Transport ($N_t$) Popularity of transport (% of population) | 615 | 85 |
| - public transport | – | 50 % |
| - pedestrian's | – | 25 % |
| - own automobile | 25 % | 25 % |
| Shops ($N_p$) | 63000 | 8750 |

Note. Results of simulations.

As detailed in (v2), agents are assumed to spend an average of 1 h in transportation (2 h each way), 2 h in public places, 8 h at work, and 12 h at home. The daily schedules of city facilities on weekdays and weekends are provided in (v2), forming the basis for each agent's schedule. These parameters adequately represent the functioning of the city and are utilized for simulation. The evaluation principle and initialization process are extensively explained in (v1).

### 3.2. GeoCity model health parameters

As evident from Fig. 2 and Table 1, the health parameters and functional dependencies of tuberculosis are well-established and defined by the World Health Organization. Thus, these values have been incorporated into the model presented here, and they are outlined in Table 3.

All other values are determined using formulas or according to the random distribution described above.

### 3.3. Determining empirical parameters of contagiousness

To determine the empirical parameter of contagiousness IR, an optimization problem was solved, aiming to minimize the standard deviation between real contagiousness data [15, 16] and the model's data over time (Equation (13)):

$$\left(con_{a,b}(t) - con(t)_{real}\right)^2 \to min a, b \geq 0 \tag{13}$$

The obtained values for the empirical parameters are: $a = 90$, $b = 50$. Fig. 3 displays the results of comparing the obtained dependencies.

Fig. 3 demonstrates a close alignment between the obtained dependency and real experimental data from comprehensive medical studies. This relationship enables us to determine the required level of contagiousness at which a patient is considered healthy. According to medical data, a patient is considered healthy 225 days after infection. Referring to the model's results (Equation 4) and the graph, at day 225, the contagion level will be $\alpha = 0.017$. Hence, we can establish that when an individual's infectivity level falls below this value, the patient is considered healthy. $\alpha$ level serves as a more appropriate criterion for determining the status of "healthy" since people can recover from tuberculosis at different rates, depending on their individual immunity levels. As a result, $\alpha$ level provides a suitable indicator for identifying a healthy individual, eliminating the need to consider future days in the assessment process.

### 3.4. Infection level determination

As mentioned earlier, determining the empirical parameter $IR$ requires running the model and monitoring the infection dynamics in the city. The reproductive number, a key criterion for tuberculosis dynamics, can be easily determined in multi-agent systems using Equation (14):

$$R = N_I(t)/N_I(t-1) \tag{14}$$

where $N_I$ – is the number of infected individuals; $t$ – time (iteration).

Based on medical studies ([6–9]; Butov D. et al., 2023 [10]), a person with tuberculosis can infect 10 to 15 healthy individuals in a susceptible environment within a year. To determine this infectivity level, a simulation was conducted where, in the event of infection, all 100 % of people transitioned into a latent state ($P_{pt} = 0$). This enabled the identification of the actual number of infected individuals by counting the number of latent people, eliminating the possibility of increased latent individuals due to new TB cases [18]. To achieve more stable results, and in consideration of a larger population, the simulation began with 44 people infected with TB ($I$) and all others in the susceptible state ($S$).

The objective was to find an $IR$ value that resulted in 440–660 agents in the latent state ($L$) by the end of a one-year simulation. During the experiment, the desired values were obtained with $IR = 0.0003 \div 0.00032$.

### 3.5. Tuberculosis spread simulation

The simulation aimed to explore the maximum scale of a tuberculosis pandemic in a healthy environment, assuming no preventive or treatment measures. It was conducted in a city modeled after Lviv with a population of 100,000 agents. The number of geo-objects in the simulation was adjusted proportionally to the real population, as shown in Table 2.

Based on medical statistics, Ukraine has 44 TB patients per 100,000 people, with over 90 % of the population in a latent state (Butov D. et al., 2023 [10]). The simulation assumed an unvaccinated city population with 0 immunity to tuberculosis, simulating a scenario of migration from a country where TB is prevalent to a country where it is eradicated, like certain EU countries.

All residents in the simulated city were initially in the susceptible state ($S$). To start the infection, 44 agents were randomly selected to be in the infected state ($I$), with a randomly determined time spent in this state $t_{st}$ within the range of 0–60 days.

Personal attributes such as immune status, health, and individual characteristics were not considered in this simulation. All agents were assumed to have the same susceptibility to tuberculosis. The simulation spanned 20 years, and it was assumed that daily population schedules remained unchanged over the years, with no consideration of new children, changes in occupations due to aging, or natural mortality from age or other diseases. If the model proves to be adequate, these factors will be taken into account in future simulations.

The impact of age-related changes in occupations is expected to be minimal, as the average number of people in schools, universities, and kindergartens will remain relatively constant despite individual changes in occupations. If the model's adequacy is confirmed, a subsequent study will consider and analyze these additional factors.

Three approximations were used to test the model's adequacy and sensitivity to key tuberculosis parameters:

1. Baseline: mortality, spontaneous tuberculosis, and relapses were not considered in the model ($P_{death} = 0, P_{pp} = 0, P_{rec} = 0$).
2. Mortality: the impact of mortality on the baseline model was investigated ($P_{pp} = 0, P_{rec} = 0$).
3. Full model: all factors, including spontaneous TB and relapses, were considered.

**Table 3**
Health parameters in the GeoCity model.

| Healthy data |
|---|
| $P_{pt} = 10\%$, $P_{death} = 10.4\%$, $P_{bel} = 10\%$, $P_{pp} = 10\%$, $P_{rec} = 14\%$ $d_{min} = 42$, $d_{max} = 56$, $md = 72$ |

Note. Results of simulations.

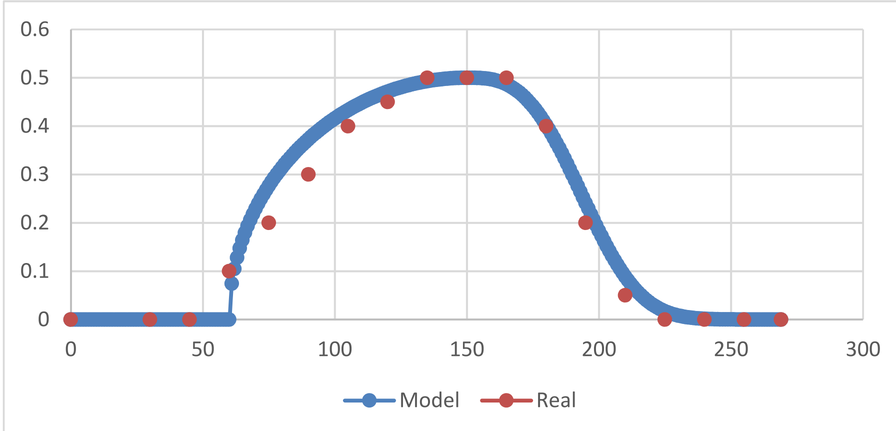


**Fig. 3.** Comparing modeled infectivity to real data.

The statistical indicators used to characterize the spread of tuberculosis were the number of infected, latent, and recovered patients, as well as the number of deaths. Fig. 4 shows the dynamics of these indicators for the baseline model.

The model demonstrates stability without random fluctuations, even with a small number of infected people. The calculation time was approximately 30 min. The graph in Fig. 4 shows an initial increase in the number of infected people during the first 2 years, followed by a gradual decline in the epidemic. The number of latent individuals rapidly increases, peaking around the 5.5-6th year of the simulation. Moreover, the number of people who contract tuberculosis continues to grow and does not reach saturation. After 20 years of simulation, the number of latent individuals is 75,169, those who have contracted tuberculosis is 19,852, and active patients are 163. This indicates that 95 % of the population (75169 ÷ 19852 = 95,027 individuals) have developed immunity to tuberculosis without considering mortality or any means of treatment or prevention.

Fig. 5 demonstrates a comparative analysis of the dynamics of TB patients in the three experiments. The results show that taking mortality into account has minimal impact on the spread of tuberculosis. Considering spontaneous tuberculosis and relapses only resulted in a slight shift in the epidemic peak by a few months. The maximum number of people with tuberculosis remained unchanged, likely due to stochastic infection parameters. Including spontaneous tuberculosis and relapses led to a stabilization of approximately 240 TB patients by the end of the simulation, representing a 50 % increase compared to not considering these factors. Notably, the maximum number of people infected with tuberculosis reached around 2.8 % of the population (approximately 2800 agents). Thus, even in the absence of active treatment, tuberculosis's maximum epidemic level is relatively low, aligning with historical data on tuberculosis spread worldwide [11,12,24].

The proposed model allows for not only statistical data but also individual-level analysis of the tuberculosis spread by specific agents. Table 4 provides a summary of the number of infected people and number of agents being newly infected. For instance, 80,858 infected agents did not infect any other agent, indicating they remained in a latent state. On average, 2 healthy agents were infected by 2005 agents. The most active patient infected 83 healthy agents. Over the 20-year simulation, a total of 162,107 cases of infection were recorded, wherein individuals transitioned from the "***S***" state to the ***L*** or ***I*** state.

The proposed model enables tracking the individual dynamics of health status for each agent. Analysis revealed that 83,808 agents were infected only once during the simulation, transitioning from "***S***" to "***L***" state. This accounts for 84 % of the population, remaining in the latent state throughout the 20-year simulation.

For instance, the dynamics of the most active agent's state changes occurred as follows: ***S- > L***, ***L- > S*** Bacteria Eliminated … ***S- > L***, ***L- > S*** Bacteria Eliminated, this pattern repeated 113 times. Thus, the most active agents are those who lose TB bacteria and are re-infected numerous times, even though they might not perceive or feel these transitions.

Another example includes an agent who changed their state 5 times: ***S- > L***, ***L- > I*** Post Primary, ***I- > R***, ***R- > I*** Recidive, ***I- > D***. This agent first

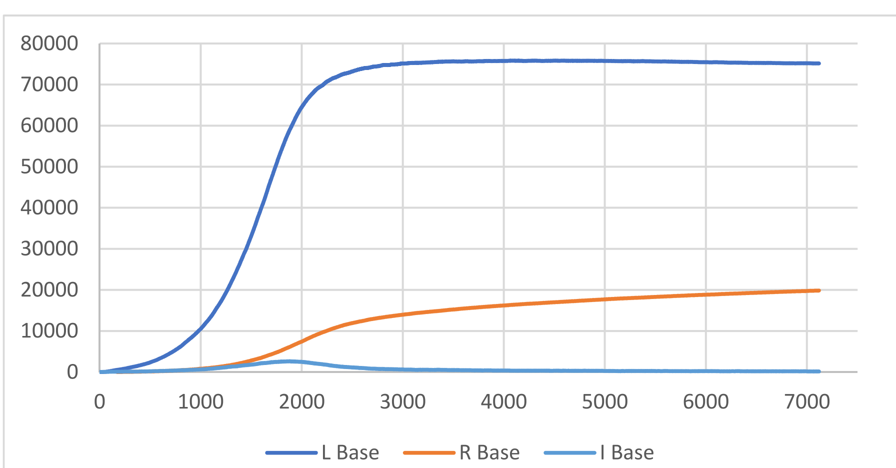


**Fig. 4.** Dynamics of sick, latent, and recovered agents in the base model.

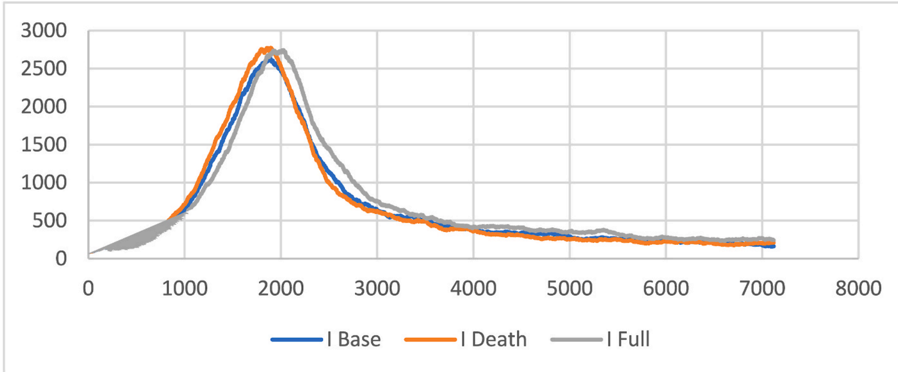


**Fig. 5.** Comparative dynamics of tuberculosis patients in 3 approximations.

**Table 4**
Number of infected cases exposed to diseased agents in the last simulation.

| Infected | Agents | Infected | Agents | Infected | Agents | Infected | Agents |
|---|---|---|---|---|---|---|---|
| 0 | 80858 | 14 | 426 | 28 | 81 | 42 | 9 |
| 1 | 1771 | 15 | 378 | 29 | 65 | 43 | 8 |
| 2 | 2005 | 16 | 331 | 30 | 82 | 44 | 6 |
| 3 | 1901 | 17 | 304 | 31 | 59 | 45 | 1 |
| 4 | 1770 | 18 | 300 | 32 | 41 | 46 | 1 |
| 5 | 1438 | 19 | 280 | 33 | 38 | 47 | 2 |
| 6 | 1277 | 20 | 234 | 34 | 37 | 48 | 1 |
| 7 | 1059 | 21 | 226 | 35 | 25 | 49 | 1 |
| 8 | 927 | 22 | 205 | 36 | 24 | 50 | 2 |
| 9 | 801 | 23 | 164 | 37 | 22 | 52 | 1 |
| 10 | 721 | 24 | 120 | 38 | 20 | 54 | 1 |
| 11 | 636 | 25 | 133 | 39 | 14 | 58 | 1 |
| 12 | 518 | 26 | 99 | 40 | 12 | 68 | 1 |
| 13 | 471 | 27 | 81 | 41 | 8 | 83 | 1 |

Note. Results of simulations.

became infected and entered a latent state, then contracted spontaneous tuberculosis, recovered, experienced a tuberculosis recurrence, and eventually succumbed to the disease.

Another example includes an agent who changed their state 5 times: ***S- > L***, ***L- > I*** Post Primary, ***I- > R***, ***R- > I*** Recidive, ***I- > D***. This agent first became infected and entered a latent state, then contracted spontaneous tuberculosis, recovered, and later contracted tuberculosis again through a recurrence. The recurrent tuberculosis proved fatal for this individual.

In addition to providing statistical information, the model enables detailed tracking of each individual's condition and health, such as their contacts, places of residence, workplaces, transportation habits, and other aspects of their life.

## 4. Conclusions

In conclusion, modeling the geospatial spread of viral infections at the city level is crucial for various reasons:

- The model's results exhibit stability and lack of significant fluctuations. The statistical values obtained for infected, latent, and recovered individuals align well with known medical data, confirming the model's adequacy.
- The proposed model allows for tracking and analyzing the life and behavior of each individual agent, enabling a thorough assessment of tuberculosis infection spread and the development of prevention strategies.
- The mathematical model can be expanded to consider other health factors and individual agent characteristics, leading to realistic modeling and evaluation of different population groups with specific TB infection peculiarities.
- The simulation time for a model with 100,000 agents is approximately 30 min, enabling parallelization of processes for modeling multiple cities, regions, or countries. This opens the possibility of using computer clusters and optimizing TB prevention strategies based on reinforcement learning neural networks.
- Indeed, creating a mathematical model using neural network technology and multi-agent modeling is a promising approach to predict the spread of tuberculosis infection in European cities with a significant influx of migrants from Ukraine.

## CRediT authorship contribution statement

**Yaroslav Vyklyuk:** Data curation, Formal analysis, Methodology, Project administration, Software. **Ihor Semianiv:** Investigation, Formal analysis, Data curation. **Denys Nevinskyi:** Investigation, Methodology, Resources. **Lilia Todoriko:** Conceptualization, Investigation, Resources. **Nataliya Boyko:** Data curation, Formal analysis, Funding acquisition, Visualization.

## 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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period", which is carried out at the Department of Artificial Intelligence Systems of the Institute of Computer Sciences and Information of technologies of the National University "Lviv Polytechnic".

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