Exploring the role of spatial configuration and human behavior on the spread of the epidemic: A study of factors that affect Covid-19 spreading in the city

Abstract

This research explores how public space, defined through the configuration of the city, and human behavior affect the spread of disease. In order to understand the virus spreading mechanism and influencing factors of the epidemic which accompanying residents' movement, this study attempts to reproduce the process of virus spreading in city areas through computer simulation.

The simulation can be divided into residents movement simulation and the virus spreading simulation. First, the Agent-based model can effectively simulate the behavior of the individual and crowd, and real location data based on residents which uploaded by mobile phone applications is used as a behavioral driving force for the agent's movement. Second, a mathematical model of infectious diseases was constructed based on SIR (SEIR) Compartmental models in epidemiology.

Finally, by analyzing the simulation results of the agent's movement in the city area and the virus spreading under different conditions, the influence of multiple factors of city configuration and human behavior on its spreading process is explored, and the effectiveness of countermeasures such as social distancing and lockdown are further demonstrated.

Keywords: *Agent-based model, Location Data, public space, epidemic, SIR*

1. Introduction

The spread of epidemics has brought threats to human society, causing huge public health risks and property losses. Because the virus is mainly transmitted through the mouth and nose, the infection between individuals contact (such as coughing and talking) can cause possible infection (WHO, 2020). It is of great significance to understand the transmission mechanism of the virus in different spaces. At the same time, it helps to formulate targeted policies to protect public health.

In the face of COVID-19, there are still gaps using ABM for infectious disease analysis, supported by real data. Technically speaking, the use of relatively new methods combined with ABM analysis of real data has practical significance. In terms of research content, the relationship between the spread of the virus and city space using COVID-19 as an example, and the relationship between the virus and human behavior (such as social distancing) need to be explored. In this research, ABM is created and combined with real mobile phone data to simulate infectious diseases in city space, while completing the research and analysis of specific issues. Using this method can better understand the mechanism and influencing factors of a new type of infectious disease. This study does not involve biology research, but focuses on simulating virus spread in city areas through modelling methods, and then analyzing its related parameters.

The simulation model consists of two parts: the first is a movement model, which is mainly driven by real residents' location data. The data is collected from map app (mobile phone location service), and the data is expressed in the form of a heat map (format: tif). Its built environment data is based on open city GIS database. In addition, the movement model is inspired by Isovist and Boids algorithms, and rules are designed to realize different movement behaviors. The second model is an epidemic model, using SIR as the main framework and using COVID-19 data as a reference for research.

2. Background

In recent years, with the development of computer technology, the use of computer simulation technology in public health related research has been increasingly applied to the spread of diseases in the region (Ajelli et al. 2010). And The agent-based model supported by data is particularly important for infectious disease research. It has higher flexibility, which is one of the evaluations of this model (Bonabeau, 2002).

Because it is based on the individual, and the behavior and state of the individual can be affected by various factors, these rules can be written into its attributes by the modeler. Individuals are distinguished, which is the basis of epidemiological research (Koopman and Lynch, 1999). In addition, this model can simulate the spread of diseases based on the connection (contact) between independent individuals (Sattenspiel, 2009). So this model is more intuitive than population-based differential equation models (Chen et al, 2015), which clearly demonstrates causality. Because the method based on equation-based cannot directly match the data to the personal level, it is impossible to achieve high-precision simulation. Therefore, the ABM method brings more details and high reliability.

Chen et al.(2015) introduces a large number of theories and cases of infectious disease analysis modelling, including examples based on agent-based model analysis. For example, Friesen and McLeod (2014) established an infectious disease model based on smartphone trajectory data, and conducted simulation analysis at the provincial and town levels. Compared with equation-based research, this individual-based model is more suitable for combining individual real data (individual behavior is driven by data).

3. Methods

The research process can be briefly described as follows: a) First, select the public space and create the built environment required for simulation, which includes borders, obstacles (buildings) and other elements; b) Create an Agent-based model Simulation model, which can be divided into two parts: movement model and epidemic model. Among them, the movement model is mainly driven by residents' dynamic location data and gives individuals more behavioral capabilities; the epidemic model is built based on the mathematical models of SIR and SEIR, which combines the real data of COVID-19. c) Simulation of virus transmission, adjust some behavior parameters and spatial parameters to simulate disease transmission under different conditions; d) Compare and analyze the influence of spatial configuration and personal behavior on virus transmission, and propose effective epidemic prevention and control strategies based on the simulation results. And verify the effectiveness of existing strategies.

3.1. Build environment: location and elements

When using Agent-based model to simulate in urban public space, the size of the area is directly related to the input samples and time, so reducing the activity space of the agent can effectively reduce the cost of the experiment. In addition, the selected area should be representative, and it is necessary to find a suitable area in city as the experimental environment.

Therefore, the selection criteria for determining the experimental area are as follows:

- The size should not be too large, as determined by the experimental cost of ABM;
- Blocks are used as the boundary conditions to control the experimental boundary;
- As a typical representative of city;
- The area should include buildings with multiple functions such as residences, schools, business districts, spaces and city centers;
- Contain transportation buildings. As an important functional building in the city, the railway station is a typical high-risk area during the virus spreading. Its population density is high and crowd exchanges are frequent. Therefore, it is a more important consideration to use traffic buildings as the site selection criteria.

Figure 1. Centre area of city

After determining the location, it is necessary to collect city information data to complete the establishment of the built environment. Since this research is based on two-dimensional virus spreading simulation, three-dimensional space environment (such as multi-storey buildings) is not considered. So only need to build the plane content of the city space environment, including: boundaries, buildings (obstacles), streets.

Figure 2. Selected city area: built environment

3.2. Data processing

The premise of using agent to simulate is to recognize individual differences, and that individuals can interact and cause disease transmission. Therefore, it is necessary to design the behavior pattern based on the individual, and set rules for the interaction between individuals, and consider the impact of time and space on the spread of the virus.

The most important driver of this movement model is location data. That is, the basic movement behavior of the agent is determined according to heat map. According to the heat map function provided by the map mobile app, the dynamic location data (picture format) of residents in a specific area can be obtained. The regional heat map data shows the population location and heat information of the real-time urban area, as shown in Figure 3.

In order to meet the simulation requirements, the heat map data for the three days from August 21 to August 22, 2020 were collected for the identified area. These three days are from Friday to Sunday, reflecting the different city states from weekday to weekend. In addition, due to the large number of people during the day, night data is not considered in this collection. The heat map used in the final simulation is the data from 8:00 am to 00:00 am on the next day, and the collection interval is two hours. Although the heat map represents a transient situation, in this simulation, each heat map represents a two-hour period.

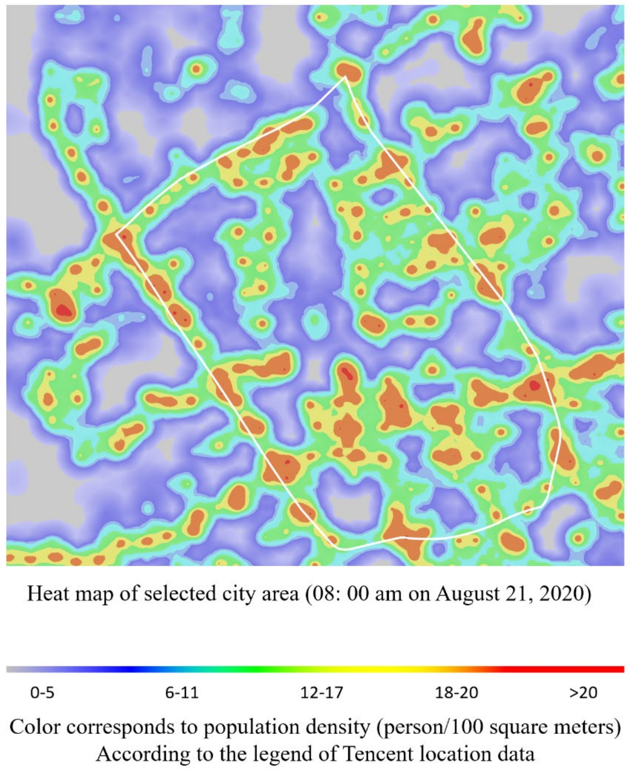


Figure 3. Heat map of selected city area

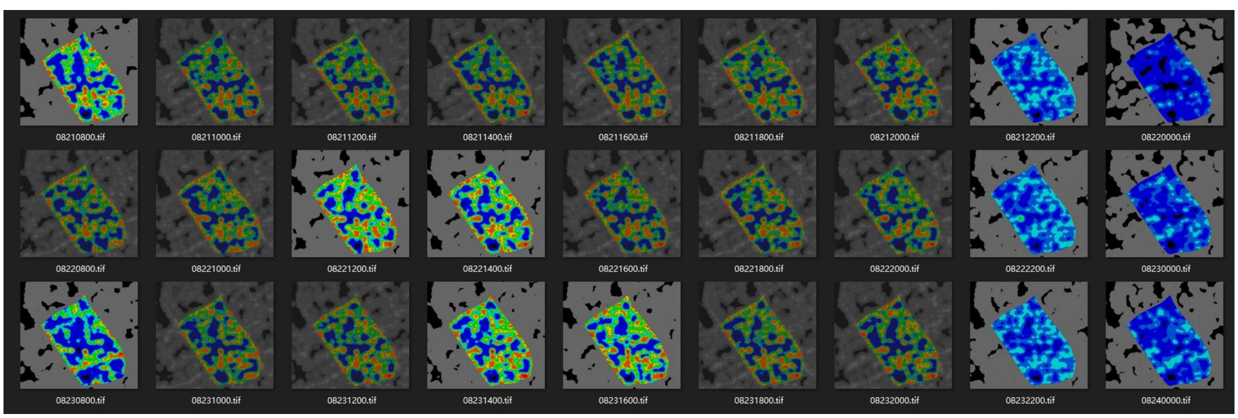
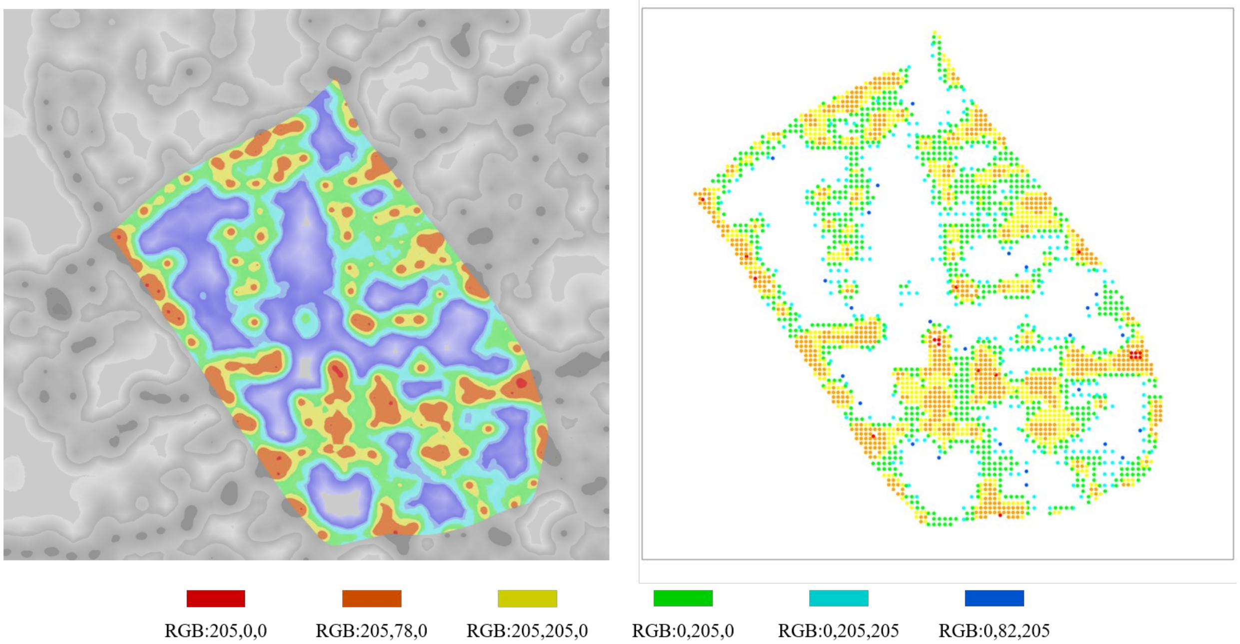


Figure 4. Heat maps for three day form August 21 to August 22, 2020

After that, the heat map data needs to be processed to complete two tasks: a) complete the initialization of the movement model; b) determine the driving mechanism of the agent's movement. Specifically, the first step is to establish a data set of resident coordinates through heat map pixels, and determine the initial position of the agent in the area through the data set (pixels are individual spatial coordinates). Second, in order to make the agent's movement driven by the data, it is necessary to make the agent gain power. Through the heat map, we can calculate the initial individual position and its potential moving direction to attractors, such as a individual (pixel) moving to the nearest densely populated area (attractors) in the next time period.

Take the heat map from 08:00 to 10:00 on August 21, 2020 as an example. By analyzing the pixels of the heat map, the pixels can be extracted proportionally as the individual coordinates based on the population density in the legend, and use the high-heat areas as the "destination", and the individual is attracted to move toward the nearby "destination" in the movement module of ABM.

What needs to be clear is that the attractor as the "destination" of the movement is calculated from the heat map of the next period.



When the initial scanning accuracy is 20000, the total number of points is 2814, the number of red points is 18, the number of orange points is 734, yellow points is 830, green points is 948, azure points is 259, and blue points is 25 (reference heat map is 08: 00 am on August 21, 2020)

Figure 5. Establish a coordinate set by different colors

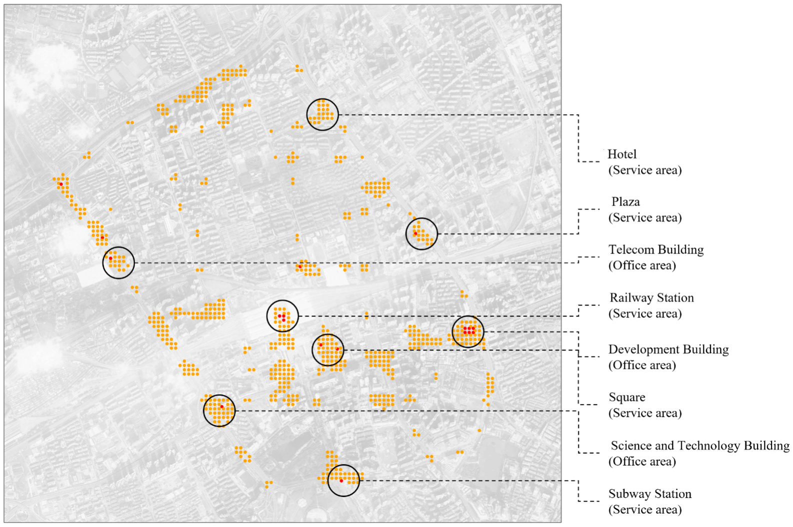


Figure 6. Pixels in high-heat areas are used as "destination"

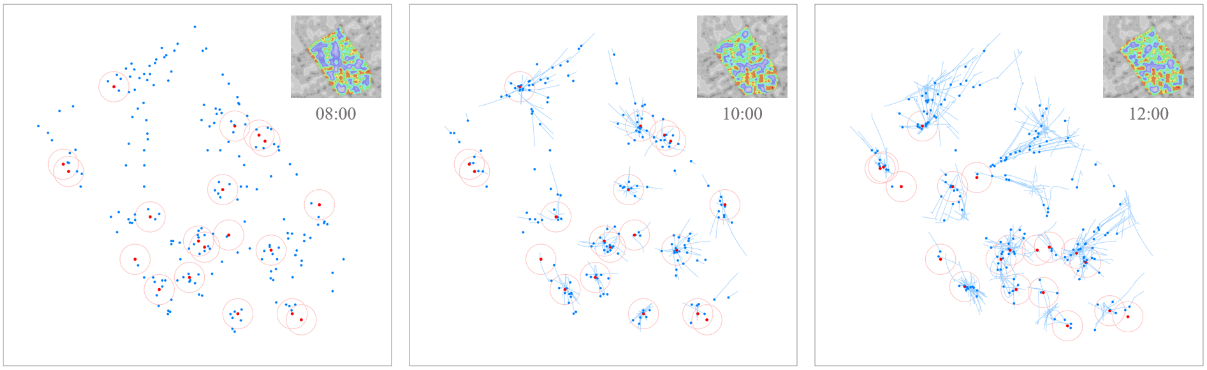
3.3. Movement model

The movement model only considers two-dimensional movement. Individuals in the movement model have basic attributes and behaviors. The attributes include the position of the individual, the direction of movement and the speed of the movement. These three are the manifestations of individual behavior in simulation.

The behavior of an individual is the rule of its movement and the reason for determining the direction of movement. The behaviors are Navigation, Group, Separate, Observation and Quarantine (Lockdown):

Table 1: Behaviors in movement model.

	Behavior	Description	Implementation	Reference
Driving force	Navigation	The individual moves in the direction of its "destination" (a nearby attraction point)	The hot area is calculated by the heat map, which is used as the input of the movement model to attract nearby individuals.	Canter and Tagg, 1975
Interaction with other individuals	Group	Individuals tend to move in groups, generally 2-5 people	Within a certain distance, individuals have a chance to move in each other's direction.	Jazwinski and Walcheski, 2011
	Separate	Social distancing between individuals	When an individual finds another individual within a certain distance, the individual moves in the opposite direction.	Hall, 1966; Gehl, 1987
Interaction with space	Observation	Observe and move in city space (built environment)	Observe the surrounding space through the line of sight (LOS) and choose the furthest direction to move.	Turner and Penn, 2007
	Quarantine & lockdown	Space limits the range of individual movement	Through a restricted space of a prescribed size, individuals in this space cannot move outside.	Stutt et al. 2020



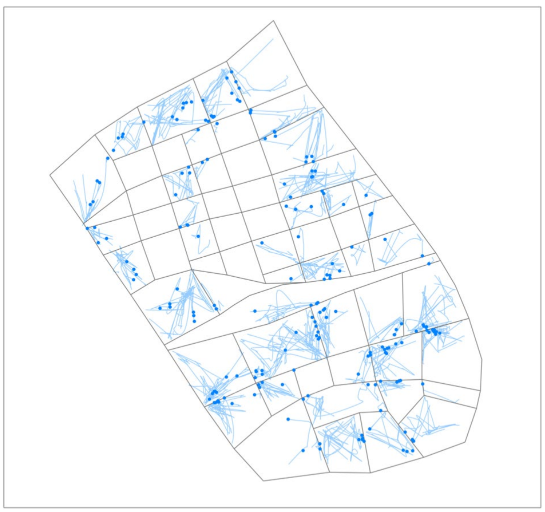
08:00 Initial state

08:00-10:00 Agent state and trajectory after the 9th exercise

10:00-12:00 Agent state and trajectory after the 9th exercise

Since each picture performs 10 operations, the agent moves 10 times. At the same time as the tenth operation, recalculate the attraction point based on the new heat map (the next moment). The agent always moves towards the nearby attraction point (refer to the heat map at 08:00 and 10:00 on August 21, 2020)

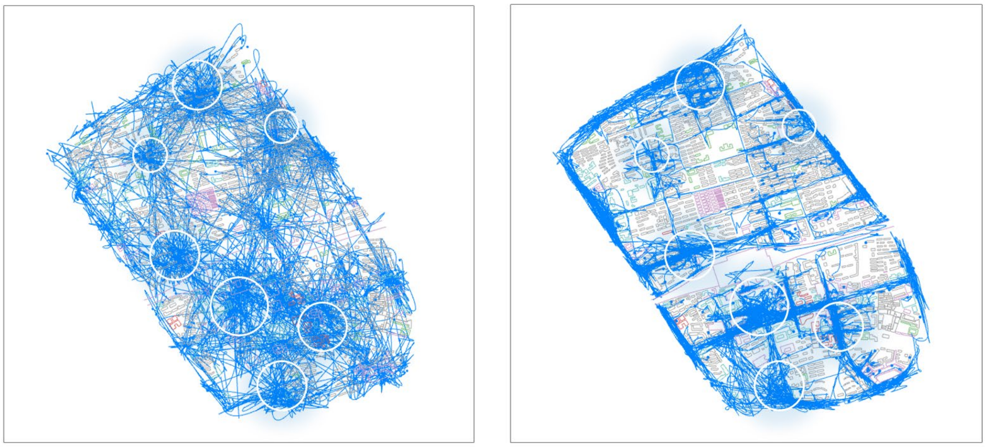
Figure 7. Simulation of individual navigation behavior



Although the agent is still affected by the heat map, it cannot escape the boundary of the city block.

Figure 8. Quarantine behavior

When considering the built environment of the city, the behavior of the agent will change greatly. If the built environment is not considered, the agent will ignore the urban obstacles and move directly to the attraction point. In this research, the built environment should be considered when analyzing the city space, while it should not be considered when analyzing human behavior.



Agent movement trajectory, regardless of built environment

Agent movement trajectory, consider the built environment

The hot area location is still similar, but the agent moves on a different trajectory

Figure 9. The trajectory of the individual in two different situations

When the movement model is executed, the specific flow chart is as follows

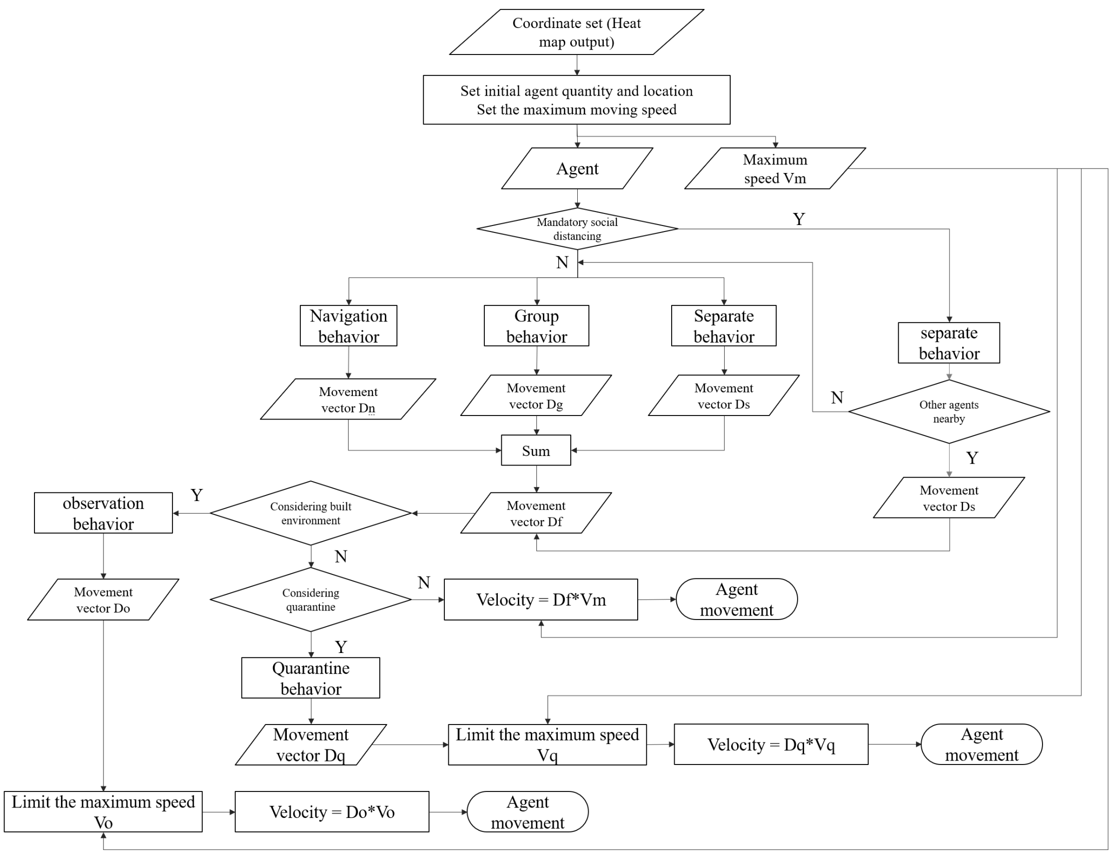


Figure 10. Flow chart of individual behavior

3.4. Epidemic model

The SIR and SEIR models are a kind of population based. Maintaining the number of existing individuals is the premise of this type of model (Beckley, 2013). That is to say, natural births and deaths are not considered. In this model, a "label" is added to each agent. This label is the individual state in the epidemic model, such as susceptible, infectious, and recovered, and the sum of the number of individuals in all states remains constant. In the initialization process, the entire population can be divided into two parts, susceptible and recovered, in proportion to the needs. The recovered here can be understood as part of the population that has acquired virus immunity. In addition, initialization can also introduce viruses in a random manner, that is, transform part of susceptible into infectious.

The parameters that directly affect the epidemic model include R0 (which represents the transmission capacity of the virus), the average time required for recovery, mortality rate, the time required for a death case, and For SEIR's unique incubation period time, etc., all parameter descriptions, values and sources are shown in Table 2.

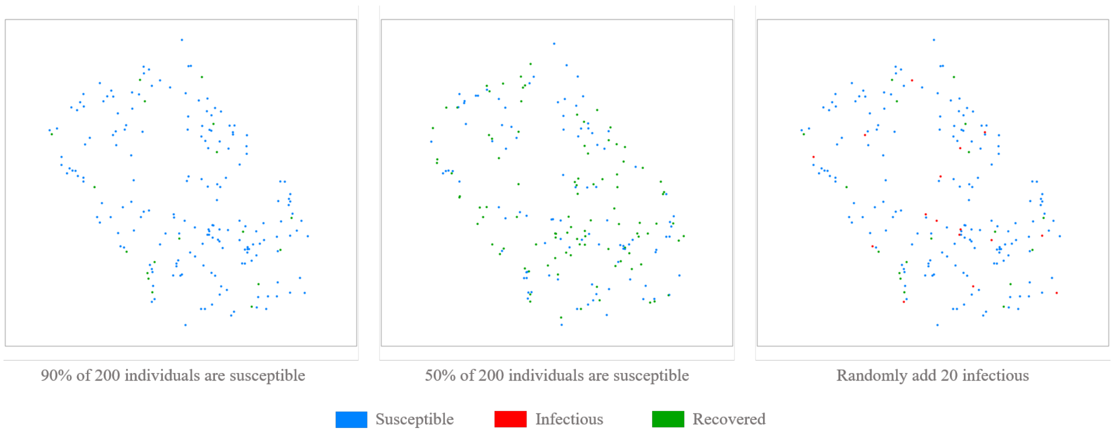


Figure 11. Individual infection status initialization

Table 2: Parameter initialization based on COVID-19.

Parameter	Description	Value	Calculation	Reference
Model Type	Choose SIR or SEIR as the basic mathematical model	SIR/SEIR	-	Kermack and McKendrick, 1927
R0	Basic Reproduction Number: used to describe the infectiousness of a disease	4	-	Description: Kermack and McKendrick, 1927 Value: Flaxman et al., 2020
Recover Time	Average duration between infectious and recovered	2-8 weeks	Each movement (each frame) represents 12 minutes. Based on the 14-day recovery duration, the **recovery rate** within 12 minutes can be calculated to be 0.0794%(12 minutes/minutes in 14 days)	World Health Organization, 2020
Death Time	Average duration between infectious and death	6-41 days, average 14 days	Based on the 6-day death time, the **death rate** per 12 minutes can be calculated as 0.0102% (the death rate per minute * 12 minutes)	Wang et al., 2020
Death Rate	mortality rate worldwide	3.3% (September 9, 2020) 5.5% (April 7, 2020)		Johns Hopkins University, 2020
Exposed Time	Duration of incubation period	1-14 days	If the exposed period is 2 days, the **exposed rate** per 12 minutes can be calculated to be 0.556% (12 minutes/minutes in 2 days)	Anna Carthaus, 2020
Average Contact	Average number of contacts in one day	5 physical contacts	Contacts are 0.0556 every 12 minutes	Davies et al., 2020
β	Infection Coefficient	-	R0 * Recover Rate	Kermack and McKendrick, 1927 Coburn et al. 2009
Infection Rate	Probability of individual infection	-	β / Average contact	Kermack and McKendrick, 1927
Infection Distance	Effective distance of infection: uncovered cough can lead to droplets travelling up to 4.5 meters	4.5 meters	-	Jayaweera et al., 2020

The epidemic model is inherited from the movement model and is relatively independent. Specifically, the agent's movement is only affected by its attributes and behaviors, while the infectious disease model shows the results of disease transmission after the agent moves, and the disease transmission itself does not affect the agent's movement mode. The model tracks the location and state of each agent, and changes the agent's "label"(disease state) under certain conditions.

The flow chart of the epidemic model is shown in Figure 12.

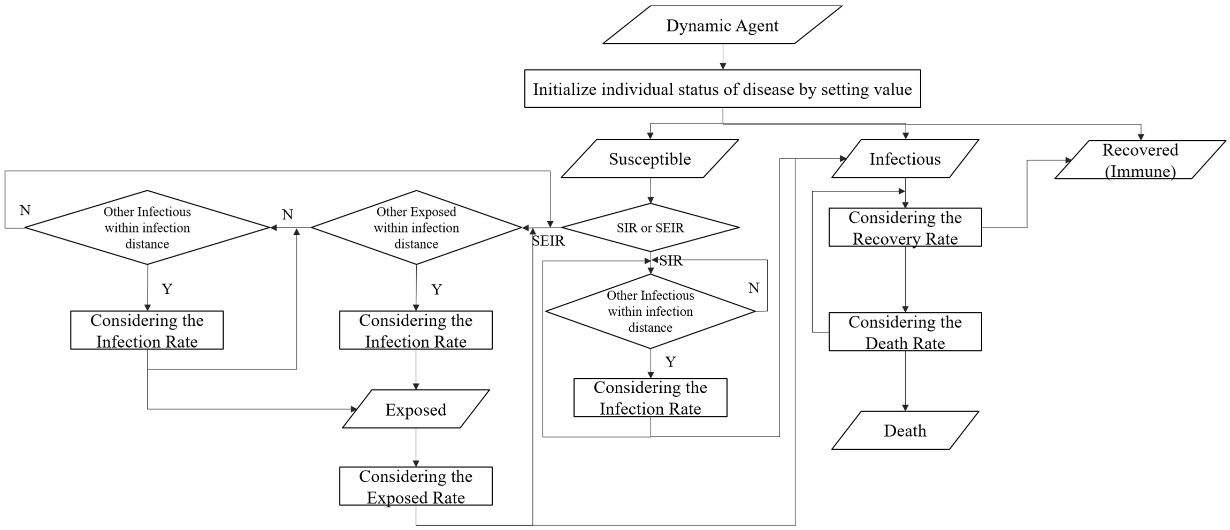


Figure 12. Flow chart of the epidemic model

3.5. Simulation model

The Movement model realizes the simulation of individual movement behaviour. The epidemic model judges and changes the individual's disease state based on the individual's movement. Based on the above two models, a complete ABM-based infectious disease simulation model is realized.

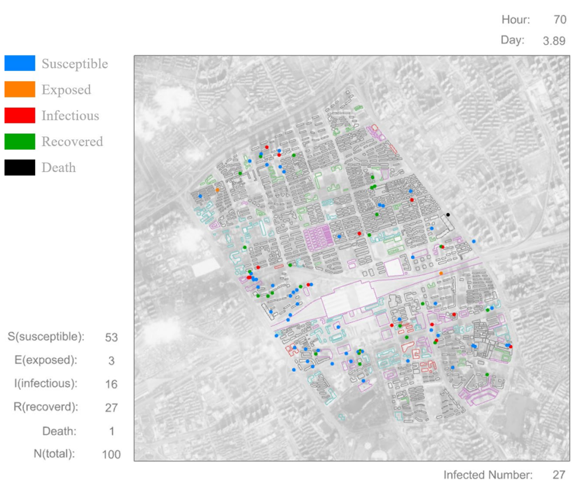


Figure 13. Virus spreading simulation interface

4. Results and Reflection

Due to the large number of model variables, it is necessary to set default parameters in simulation experiments for different factors. The parameters here consider people's daily behavior (normal movement, stay, social distance) and normal operation of public spaces (not considering lockdown, etc.), as shown in Table 3:

Table 3: Default parameter setting.

Category		Parameter	Description	Value
Location Data		Initial coordinate set	Calculated based on the heat map. Potential initial position of the agent.	-
		Attractor	As the "destination" of the agent, it is calculated based on the high heat area of the heat map. Determine the number of attraction points as needed.	Quantity: 50
				Factor: 0.5
Movement Model	Individual and Behavior	Number of Agents	Randomly select from the Initial coordinate set.	Set as needed (200-1000)
		Location of Agents		From Initial coordinate set
		Maximum Speed of Agent	According to the average human moving speed	Max speed: 1.5 m/s
				Stationary factor: 10
		Group Parameter	Agent aggregation behavior	Group Distance: 7m
				Factor: 0.5
				Probability: 50%
		Social Distancing Parameter	Keep a certain distance between agents	Social Distance: 1.2
				Factor: 0.5
	Built Environme nt and Space	Observation Parameter	Use Line of Sight to observe the built environment and move	Observation Range: 20
				Observation Detail: 3
		Quarantine Parameter	Movement area limitation	Set as needed
Epidemic Model		Initial susceptible number	-	Set as needed
		Initial infectious number	-	Set as needed
		Other Parameter(R0 etc.)	-	See table 4.2
Simulation Control		Simulation environment	-	City area, Jianghan District, Wuhan
		Simulation Duration	Set each heat map to calculate 10 times. Since each heat map represents 2 hours, each calculation (agent movement) represents real time 12 minutes	Set as needed (7 days)

4.1. The impact of city spatial configuration

(1) City spatial configuration

When analyzing the impact of different space configurations on the spread of the virus, the typical space of the area is divided into different parts. In terms of functional characteristics and spatial forms, these typical spaces are newly built communities, old communities, service and commercial areas, office areas, school areas, and hospital areas. The reason for classifying according to function is that different function spaces have different urban area characteristics (form, organization, density). This experiment is not about the relationship between space function and virus transmission, but the influence of space configuration embodied by this function on virus transmission. A typical representative of the space based on these six types is shown in Figure 14.

Figure 14. Six typical spaces in cities

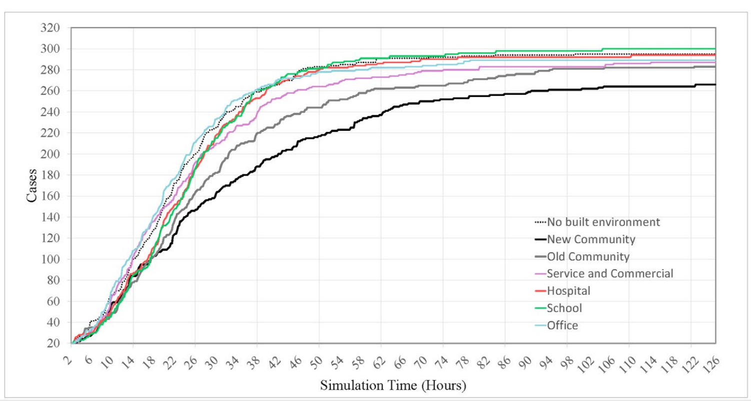
These six typical spaces have similarities and differences in their shape, size, and density. Based on the relevant information of the area, these spatial characteristics are as follows:

Table 4: Characteristics and attributes of six typical spaces.

Configuration Type	Representative	Layout	Shape	Scale	Density
Type1	New Community	Centralized	Grid	Large (151869m²)	Low(22%)
Type2	Old Community	Centralized	Grid	Medium (99655m²)	High(37.2%)
Type3	Service and Commercial	Centralized	Linear/ Fishbone	Medium (106438m²)	High(34.5%)
Type4	Office	Centralized	Linear/Grid	Large (146031m²)	Low (23.3%)
Type5	School	Distributed	Scatter	Small (61854m²)	Low(17.9%)
Type6	Hospital	Distributed	Scatter	Small (14450m²)	High(47.2%)

The above data is only for this area, and it is believed that the same type of space has similar spatial characteristics. However, this space is only a typical case and does not have universal applicability. Based on this, for these six different types of spatial configurations, when only the same type of built environment is considered, simulations are performed separately. The simulation results and the line graph of the infection cases are as follows:

a. Epidemic simulation only consider the same space type



b. Infectious cases of different space types

Figure 15. Virus spreading simulation in six typical spaces

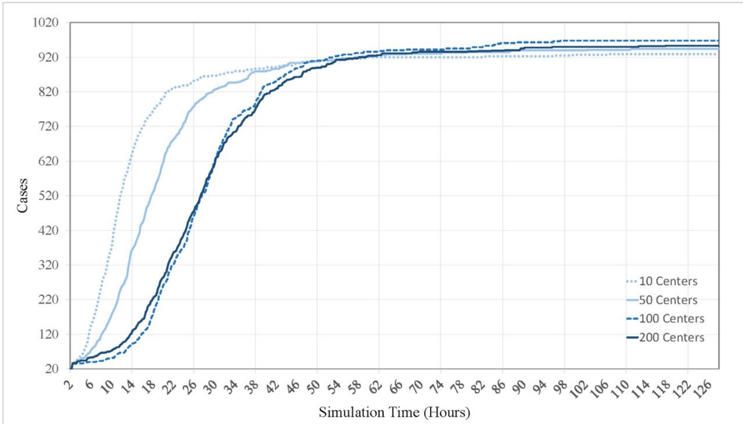
In summary, from a larger scale (city area), the concentrated spatial layout may reduce the total amount of virus infection. The net-shaped space (multiple cross paths) will also slow down the spread of the virus to a certain extent and reduce the amount of infection. The linear and fishbone-shaped space (single path) will accelerate the spread of the virus in the early stage. The larger space area (more buildings and complex urban environment) will also reduce the cases of virus transmission, which may be related to the limitation of space on the speed of individuals. From a small scale (community) point of view, there are more cases of infection in areas with higher density, and the spreading process is faster, which may be related to the limitation of local space on the range of human movement.

(2) City decentralization strategy

In this project, the agent's "destination" (attractor) is obtained through the calculation of the heat map. It reflects the attraction of the hot areas of the heat map to individuals. Fewer city centers will lead to the tendency of individuals to centralize and also mean larger-scale gatherings. On the contrary, more urban centers are a decentralized approach to a certain extent. Based on this, conduct experimental demonstrations and analyze the impact of decentralization on the spread of the virus.

The influence of different numbers of city centers on the spread of the virus is analyzed.

a. Epidemic Simulation: setting different numbers of city centers (attractors)



b. Infectious cases in a city area with multiple centers

Figure 16. Virus spreading simulation with multiple centers

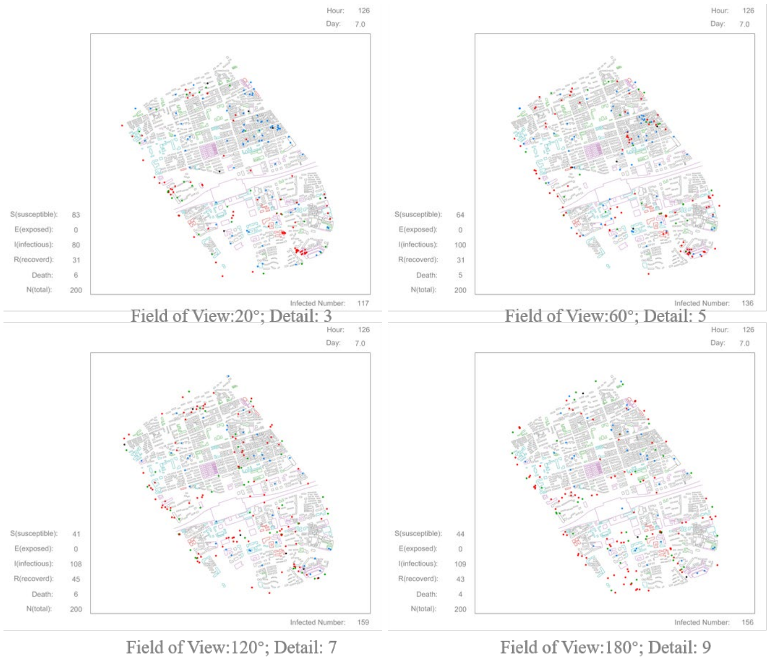
It can be seen from the simulation results that the number of urban centers directly affects the speed of early virus transmission, and fewer urban centers means faster infections. the virus transmission rate is basically inversely proportional to the number of centers. The less the number of centers, the faster the virus spreads. But when approaching a certain number, its spreading rate remains basically unchanged. It can be seen that the number of multiple centers may lead to relatively more infections, but the overall difference is not obvious.

Therefore, the decentralization strategy, or multi-centralization, may be an effective means to delay the early spread of the virus, but its effectiveness is reflected in a certain number of ranges. It should be noted that this strategy may bring more infections.

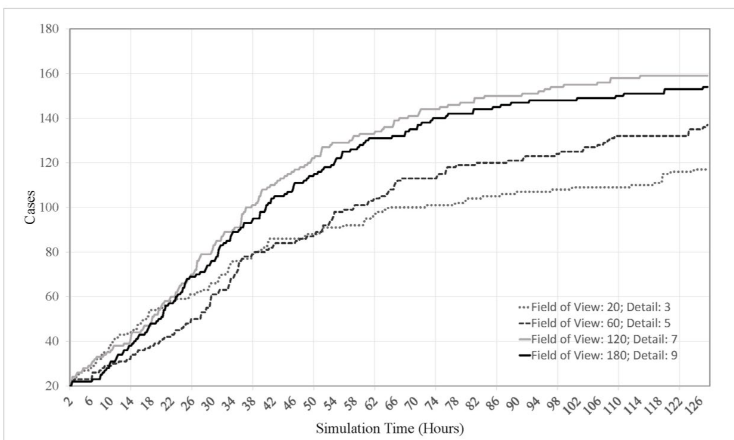
(3) Interaction of sight and city space

In this study, vision has two important parameters, in addition to the field of view (Field of View), there is also the degree of detail of observation (Detail). These two parameters directly affect the interaction between individual vision and the city space. In other simulations, in order to ensure that the movement of the individual is driven by the heat map data, it should not deviate significantly from the attraction of the attractor, so the individual's observation range and Detail value are set lower. However, when analyzing vision alone, we set up several different combinations of vision parameters to analyze how it affects the movement of individuals and thus the spread of the virus.

The visual ability increases with the increase of the parameter value, and the greater the impact on the movement, the simulation results are as follows：



a. Epidemic Simulation: setting different visual parameters



b. Infectious cases in a city area with different visual parameters

Figure 17. Simulation results with different visual parameters

From the above simulation analysis, it can be seen that as the field of view increases and the observation details increase, the overall infection cases show an increasing trend, and the infection rate also increases to a certain extent. Among them, the change process of 20 degrees, 60 degrees, and 120 degrees is particularly serious. The final infection cases are 117, 136 and 159. The growth rate was 16.2% and 16.9%.

This shows that under the condition of having a wider field of view (greater than 120°), individuals will explore the city sufficiently, which may cause faster and more infections. With a smaller field of view, individuals are more likely to be restricted by space obstacles, with smaller moving range and speed, and less infection. And it shows that when the field of view exceeds a certain upper limit, the individual's space exploration behavior may not have more obvious changes, and the impact of changes in the field of view on the spread of the disease will also be reduced.

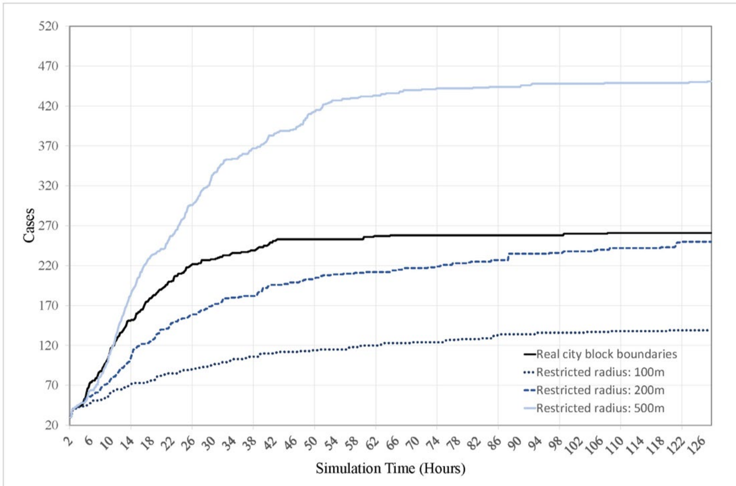
(4) Partial Lockdown and quarantine in city area

City lockdown is a restriction policy implemented on a larger scale (city level), while the very small-scale spatial restriction belongs to personal quarantine. Whether an isolation strategy that allows individuals to move within a certain range can be adopted, which not only guarantees the freedom of individual movement to a certain extent, but also effectively limits the spread of the virus.

This study chose two space restriction strategies. One is based on the real geographic environment and limited by blocks; the other is space limitation based on size, which analyses the impact of the size of the limited space on the spread of the virus.

This simulation only considers the limited space and does not consider the impact of other built environments. Virus transmission simulations are carried out for space constraints of different scales, and the results are as follows:

a. Epidemic Simulation: setting different restricted areas



b. Infectious cases in a restricted areas

Figure 18. Virus spreading simulation with restricted areas

As the radius of the restricted area decreases, the speed of virus transmission and the amount of infection have decreased significantly. In general, the blockade strategy based directly on community boundaries will cause the virus to spread quickly in early stage, but the total amount of infection will not increase significantly. The blockade of areas less than 200 meters can effectively slow down the spread of the virus and greatly reduce the total amount of infection

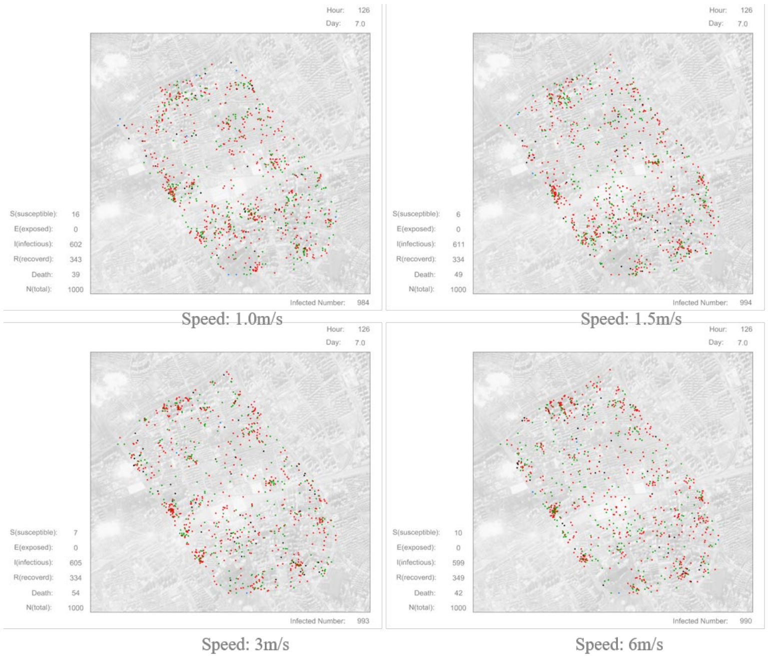
4.2. The impact of movement behavior

(1) Movement

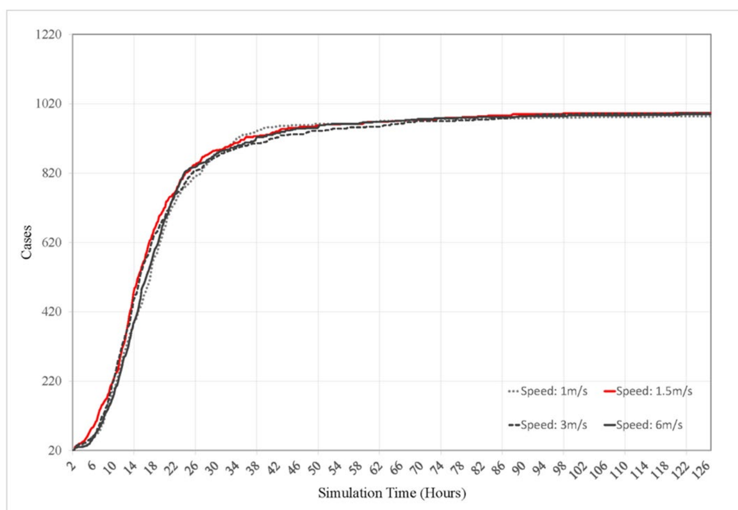
Speed, as one of the most important parameters of movement, describes the state of a person to a certain extent. Speed changes will also affect the speed of virus spread.

The average walking speed of a person is 1.5m/s. Other studies have pointed out that the average movement speed of the elderly is 2.80mph to 2.95mph(1.25m/s-1.32m/s), while the movement speed of young people is 3.31mph to 3.37mph(1.48m/s-1.51m/ s) (TranSafety, 1997). Therefore, when considering lower movement speeds, the parameters are specified at 1 m/s. In addition, considering the individual jogging situation, Keller (1996) pointed out that the average running speed of the individual is 3.0-3.4m/s (female) and 3.4-3.8 m/s (male). Therefore, a running speed of 3m/s is also considered in this experiment.

The simulation results according to different speeds are as follows:



a. Epidemic Simulation: setting different Movement speed



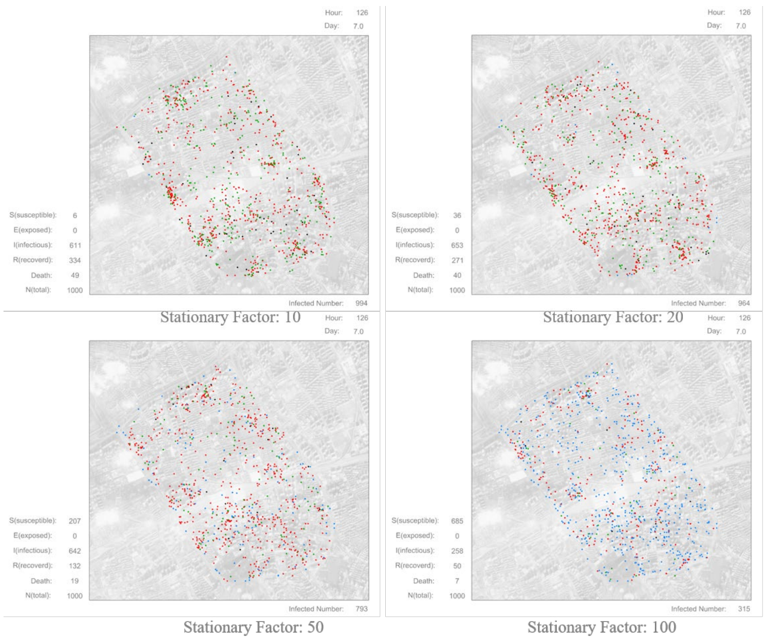
b. Infectious cases with different movement speed

Figure 19. Simulation result of movement with different speed

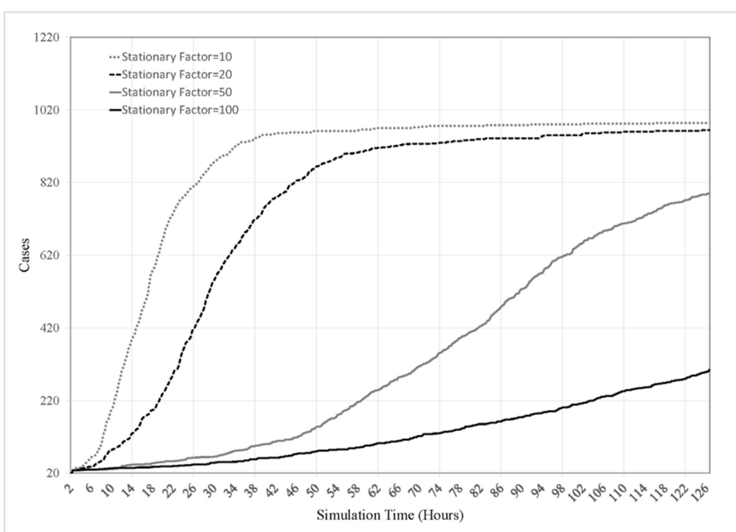
On the whole, the movement of individuals at different speeds did not result in significant differences in the spread of the virus. Under the four moving speeds, the virus transmission rate and the final virus infection cases are relatively close. It is not expected that faster movement speed will speed up the spreading process. The possible reason is that, without considering the built environment, the speed limit will not affect the individual's movement mode, and the movement path based on the heat map will not change. So it does not change the chance of individual contact, so the infection results are similar.

(2) Stationary behaviour

In human behavior, stationary activity is an important part. Such as waiting for the bus, rest, etc. And this experiment is to analyze how the stay of an individual affects the process of virus spreading. In order to increase the probability of staying, the stationary parameters are adjusted here. A larger stay parameter will make the individual have a higher probability of staying behavior. The simulation results are as follows:



a. Epidemic Simulation: setting different Stationary Factor



b. Infectious cases with different Stationary Factor

Figure 20. Simulation with different stationary factors

A larger Stationary Factor will significantly slow down the spread of the virus. When the Stationary Factor is 10 and 20, the virus spreads quickly in the early stage. At the 50th hour, its infection has reached 962 and 865, which are close to the peak. However, when the Stationary parameter is 50 and 100, the spread of the virus is significantly reduced. At 50 hours, the infection amount is 148 and 80, respectively.

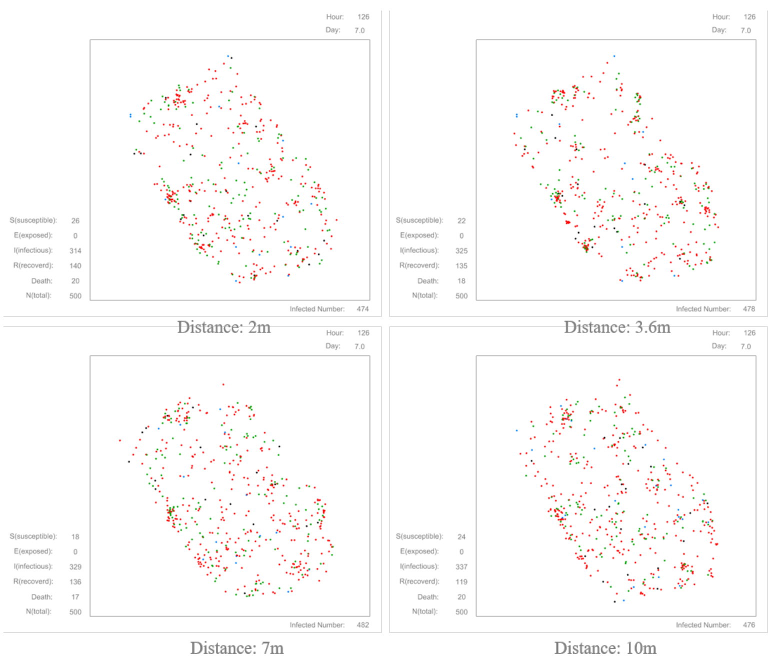
It shows that staying behavior has a small impact on the final total amount of infection, and can only reduce the number of infection cases within a limited time, but it will greatly delay the time of virus spreading.

(3) Social distancing

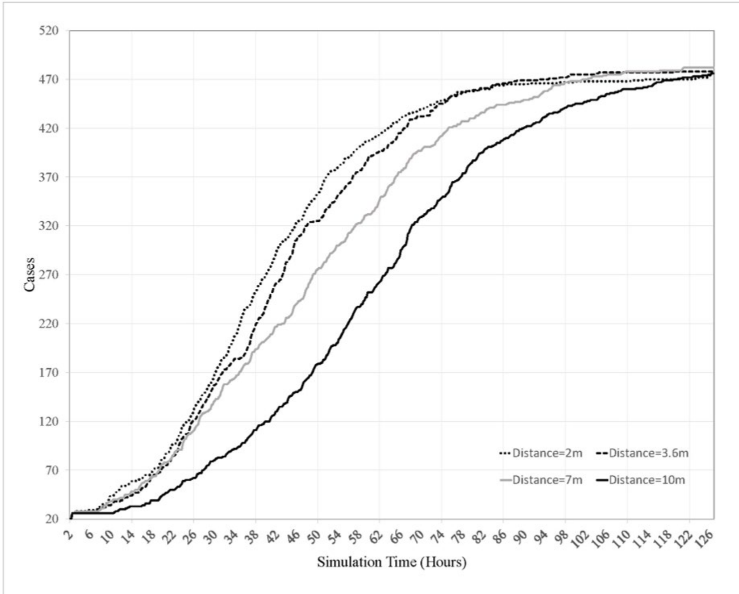
Social activities, especially social with distancing, are another common behavior of people in public environments (see chapter 2.1.1). In the face of COVID-19, social distancing methods are also adopted to deal with the spread of the virus. For example, the UK NHS (2020) recommends a social distance of 2 meters, while the WHO (2020) recommends a social distance of 1 meter.

This experiment analyses the differences between different social distances in the face of the epidemic. The social distance control here is a non-mandatory control. Which means after entering the virus transmission distance, individual found that the distance is too close and then reacts.

The simulation results of different social distances are as follows:



a. Epidemic Simulation: setting different distances between individuals



b. Infectious cases with different distances

Figure 21. Simulation result with different distances

From the above results, we can see that different social distances will obviously affect the speed of virus transmission, but the total infections are almost the same. The increase in social distance from 2 meters, 3.6 meters, 7 meters to 10 meters slows down the spread of the virus. It shows that social distance has effectively controlled the spread of the epidemic. And as the distance becomes larger, the effect becomes better. However, the total amount of infection cases at different distance is basically same. The reason may be this simulation is based on a fixed area while the population remains the same, that is, individuals are moving in a closed space. Therefore, the spread in this kind of enclosed space only affects the speed of the infection, and cannot avoid the spread of the virus. The total infection volume is almost unchanged.

5. Conclusion

After simulation and experiment, the conclusions are as follows:

- Discussing virus spreading in city space should start from two scales: at large scale (city level), the space with decentralized characteristics (network form, distributed layout) will slow down the speed of virus transmission; but concentrated Features (linear form, centralized layout, high density) space will reduce the total amount of infection. From the perspective of small scale (community level), spaces with concentrated characteristics (centralized layout, linear, high-density, etc.) will cause faster and more infections, and vice versa.
- Small-scale space restrictions will accelerate the speed in early stage of virus transmission. This kind of regional restriction measure is actually aimed at controlling the total amount of infection to avoid spreading on a larger scale.

- "Multi-centre" strategy of dispersing the population can delay the spread of the virus, but the effectiveness of this effect is also within a certain range of "multi-centre" numbers. But it should be noted that this method may bring slightly more infections.
- The wider the view, the more adequate the exploration of urban space. This kind of exploration is essentially different from the movement based on the heat map. It is kind of "Aimless" movement behaviour, similar to roaming. It will cause faster and larger infections. However, when the field of view is small, that is, when performing "purposeful" behaviours that are mainly driven by heat maps, the early virus spreading speed is faster, but the total amount of infection is small.
- The change of individual movement speed basically does not affect the virus transmission process. This speed refers to normal movement, not low speed or stay. This is because the individual's behavioural trajectory has not undergone a fundamental change. In a fixed area, individuals will still gather and cause the virus to spread, which has no essential relationship with individuals taking different vehicles (not considering the closed transmission of vehicles).
- Higher staying probability and low-speed movement would significantly slow down the spread of the virus, but did not change the number of spreads. This approach will only delay the spread of the virus, not stop it.
- Social distancing strategy can effectively control the spread of the virus. As the distance between individuals increases, the spread of the virus becomes slower. However, the total amount of infection will not change, just like the stationary behaviour of individuals, it will only delay the spread of the virus and will not avoid the spread of the virus.

The study itself has certain limitations. In terms of research methods, the simulation is based on the heat map. The heat map (attraction point) is the main driving force of the individual, rather than based on real trajectory data. At the same time, in this model, a variety of other behaviours are given to the individual, which lead to differences between the individual's movement and the real behavior, and this difference will bring uncertainty in the results. In terms of research objects, this research is based on a specific city area. All conclusions can only be used as a reference rather than universal application. At the same time, the population-based infectious disease model does not consider changes in the number of people in the area, which is an ideal simulation. Besides, for the infectious disease model, since there is no precise mathematical simulation description and biological analysis for COVID-19, there will be certain limitations in its spreading mechanism. In terms of research content, personal behavior only focuses on human movement behavior, and does not involve strategies such as wearing masks and hands washing.

To sum up, this study is based on real data, applying agent-based model, to create individual movement model and epidemic model. Then conduct a large number of simulation experiments based on it. Study the virus spreading process in different situations. The influence of city factors, defined by spatial configuration, and individual movement behaviors on the spread of the virus is analyzed. These research results can be used as a reference for dealing with the spread of the epidemic.

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