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COVID-19 Spread Simulation in a Crowd Intelligence Network

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ABSTRACT

In this paper, the Crowd Intelligence Network Model is applied to the simulation of epidemic spread. This model combines the multi-layer coupling network model and the two-stage feedback member model to study the epidemic spread mechanisms under multiple-scene intervention. First, this paper establishes a multi-layer coupled network structure based on the characteristic of Social Network, Information Network, and Monitor Network, namely, the Crowd Intelligence Network structure. Then, based on this structure, the digital-self model, which has a multiple-scene effect and two-stage feedback structure, is designed. It has an emotional state and infection state quantified by using attitude and self-protection levels. This paper uses the attitude level and self-protection level to quantify individual emotions and immune levels, and discusses the impact of individual emotions on epidemic prevention and control. Finally, the availability of the Crowd Intelligence Network Model on the epidemic spread is verified by comparing the simulation trend with the actual spread trend of COVID-19.

KEYWORDS

COVID-19; epidemic spread simulation; multiple scenes; multi-layer coupled network

The world is still shrouded in the haze of the COVID-19 pandemic[1]. In suppressing the epidemic, research on the transmission mechanisms of epidemics has been increasing. Among them, simulation, as an important supplement to the two traditional verification methods of theoretical reasoning and experimental observation, has attracted considerable attention[2].

The international community has never stopped studying the transmission mechanisms of epidemics. The cost of repeated experiments is unacceptable for the study of epidemics; thus, the use of models is important for the study of the epidemic. Researchers have built epidemic models and studied the transmission mechanism of viruses through computer simulation. Based on the granularity of the simulation model, the epidemic model can be roughly divided into two levels: coarse-grained model and fine-grained model.

The coarse-grained model is often used to analyze disease development quantitatively through dynamic methods such as ordinary and partial differential equations. The most classic model is SIR (S-susceptible, I-infected, R-recovered), which was proposed by Kermack and McKendrick[3] in 1932. Subsequently, researchers have established various models by using different transmission characteristics of viruses, such as Susceptible-Infectious model (SI), Susceptible-Infectious-Recovered model (SIR), and Susceptible-Exposed-Infectious-Recovered model (SEIR). Coarse-grained models focus on the population infection status. Considering that the parameters in these models are determined, actual data can be easily fitted.

The compartment model can approximate the epidemic development actual statistical trend to a certain extent. On the contrary, the mathematical model can hardly consider social relations and spatial movement of people. In addressing this problem, the multi-population model is developed on the basis of the compartment model. However, it remains a macro model based on the evolutionary derivation of differential equations.

1 Related Work

Complex individual behavior often plays an important role in the spread of epidemics. Researchers have begun to build fine-grained models of simulation to describe such complex individual behavior.

The fine-grained model regards individuals as finite states and behavior sets. Individuals have heterogeneous characteristics, and the final simulation results are affected by dynamic interactions among individuals. Most of the models, which are built on the basis of the Cellular Automata Model and Multi-agent Model, belong to fine-grained models[4,5].

The Cellular Automata Model is a dynamic system with time and space discrete, and the system is constructed using a "bottom-up" method. It is a computational mathematical model that simulates complex structures and processes. This model consists of four parts, namely, "Cell", "Cell space", "Cell neighbor", and "Cell rule", where "Cell" is a certain set of states. The relationship among the constituent elements of Cellular Automata is shown in Fig. 1.

With regard to model principles, Cellular Automata is suitable for individual-based research, for example, the study of epidemic spread. During the epidemic, the virus is spread by the Social Network, which is formed by human contact. It is similar to the

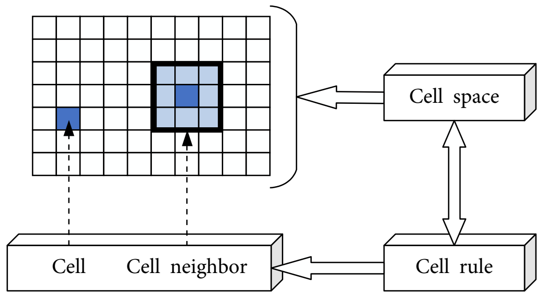

Fig. 1 Schematic of the Cellular Automata Model.

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concept of "Cell", that is, each grid point in the Cellular Automata Model can only have a specific state. However, the grid is based on "Cell space", which is not enough to describe complex social relationships formed by the community structure, such as individual occupations, interests, and social relationships[6–8].

The agent-based simulation model is also a "bottom-up" building method. It focuses on describing the behavior and interaction of each agent[9]. The term agent is used to represent an entity or individual with intelligence in the real world, such as a person in a society. Each agent is in the same environment and has individual goals, behavior, and skills[10]. A multi-agent system aims to decompose large-scale complex systems into simple and small-scale systems, which can directly coordinate and interact[11]. The principle of the Multi-agent Model is shown in Fig. 2.

Agents provide their behavioral reflection of the environment, which will cause changes in the environment. During epidemic simulation, the Transmission Evolution System, consisting of the virus, susceptible persons, and the environment, can be constructed by defining the agent response behavior to the virus and spatial movement rules. Researchers can analyze the spread of epidemics in individual granularity through this system. However, the Multi-agent Model can only describe simple social relationships, and the agent is only affected by a single environment. Furthermore, simulating complex relationships and interaction rules in multiple scenes is difficult.

In using the network to describe complex relationships, several researchers focus on the influence of epidemic spread in different network topologies, for example, Small-world networks[12], Scale-free networks[13,14], Local-world Evolving networks[15,16], Clustered networks[17,18], and other special network topologies. Some researchers focus on the threshold of the influence of disease transmission by different network degree distributions and correlation coefficients[19,20]. These studies provide a theoretical basis to use complex networks and construct epidemic models.

Network dynamics have complex characteristics, and it is a kind of nonlinear scientific research[21]. In the network dynamics model, the network structure can be described by the graph defined in mathematics and the node state transitions by certain local rules in the network. The network dynamics model has a fixed structure and rule characteristics. However, each member in a large-scale system presents different behaviors because of various uncertain external factor combined effects, but it conforms to certain rules. This finding is consistent with the real spread of epidemics in Social Network. Thus, the simulation model is built by network dynamics.

In recent years, the network model has attracted considerable attention from researchers because it makes up for the deficiency of the fine-grained model. Researchers build appropriate epidemic dynamics models to explain the transmission phenomenon of the virus. For example, Colizza and Vespignani[22] used a metapopulation model to study the impact of different travel modes on the epidemic spread in a heterogeneous connected network environment. Funk and Jansen[23] analyzed the spreading behavior of strains under overlay networks. Chen and Li[24] and Gómez-Gardeñes et al.[25] studied the dynamic behavior of sexually transmitted diseases in the complex network. Jin et al.[26] studied the dynamic behavior of the H1N1 influenza network model.

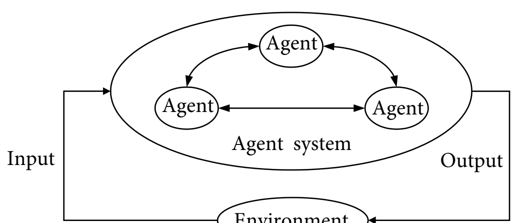

Fig. 2 Schematic of the Multi-agent Model.

Researchers have conducted in-depth studies on the spread mechanism of COVID-19. Kucharski et al.[27] analyzed all positive cases of Wuhan using mathematical models. Gatto et al.[28] used the extended SEIR model to prove the critical role of asymptomatic and symptomatic infected persons during the COVID-19 outbreak. Ndaïrou et al.[29] presented an autonomous model to study the spread of COVID-19. With regard to prevention and control of epidemic, Prem et al.[30] analyzed the controlling status of COVID-19. Hellewell et al.[31] studied the effectiveness of the isolation procedure for COVID-19. Mandal et al.[32] proposed a mathematical model to mitigate disease transmission by introducing a quarantine class and governmental intervention measures, such as lockdown, media coverage on social distancing, and improvement of public hygiene.

The complex network model can describe the complex social relationships of individuals. However, it hardly considers individuals' feedback and multiple influences. Human beings are social creatures, and they cannot simply be regarded as independent individuals. The essence of man is the real social connection of man[33]. Man plays different roles in different scenes simultaneously and maintains a complex network of relationships in the real world. Thus, the Crowd Intelligence Network Model is built to quantify individual attitudes and behavior. Moreover, it describes human social characteristics through a multi-layer coupled network.

Studies on the Crowd Intelligence Network Model are obtained from Crowd Science and Engineering, which explores the basic principles and laws of the collective intelligence system[34,35]. Researchers have mapped individuals in the real world into digital space, discussed the mechanisms of information diffusion, and analyzed the multi-information disseminations in the Crowd Network[36,37].

This paper constructs an epidemic model with multiple-scene intervention and analyzes factors influencing the spread of viruses through simulation. The fine-grained model uses algorithm optimizations and multimachine technology distribution to address challenges such as many parameters and complex calculations in simulation[38].

2 Crowd Intelligence Network Model

This paper proposes an epidemic spread model with a multi-layer coupled network structure, namely, Crowd Intelligence Network structure. In addition, the member in this model is called the digital-self unit. This unit simultaneously exists in multiple networks as the minimum granularity unit of simulation. Three network layers correspond to three devices in the unit model. One specific layer interacts with other layers through the unit model. Moreover, the infection state of every unit in this generation is generated by the joint process of all devices of the unit model. The multi-layer coupled network model nested the digital-self model, which has a two-stage feedback structure to simulate epidemic spread.

2.1 Crowd Intelligence Network structure

In real life, people can interact with others in multiple scenes. They can carry out actual physical contact or a series of information exchanges. Based on different interaction factors, this paper divides the spreading process of the epidemic into three basic scenes. It uses three different network structures to describe the interaction relationship between individuals in different scenes. Figure 3 shows the relationship of individuals in multiple scenes.

The Social Network layer describes the physical contact among the members, showing the community characteristics. In the epidemic spread scene, a virus spreads through physical contact among individual members. Individuals in the Social Network have four states: susceptible, infectious, diagnosed, and recovered[39]. Moreover, the virus is affected by individual self-protection levels.

The Information Network layer describes the information connection among individuals. It also presents the characteristics of the small world. In the information dissemination scene, the epidemic message is disseminated through information among individuals. Individuals in the Information Network layer have four emotional states: indifference, worried, afraid, and numb[40]. These states represent four different stages of attitude level. Individual infection probability at the Social Network will decrease with the increase of attitude level.

In the epidemic monitoring scene, the epidemic inspection system presents a hierarchical structure. Each inspection department monitors the epidemic situation and reports the epidemic development situation level by level. The root inspection department makes appropriate decisions based on the situation from the lower inspection department and orders the leaf-level inspection departments to implement such decisions. All the inspection departments form a hierarchical network with monitored individuals.

2.2 Digital-self model

The individual member of the Crowd Intelligence Network is called the digital-self unit. It has a two-stage feedback structure, which can simulate member self-regulation and the influence from other members in the Crowd Intelligence Network structure. In this paper, the digital-self unit has different attributes and behavioral tendencies, namely, self-endowments. The actual behavior of the digital-self unit is determined by the individual behavior tendency and is affected by the behavior of other units in the multi-layer network. Figure 4 describes the model structure of the digital-self unit. Each unit comprises pattern, connector, influencer, decider, monitor, and executor. The actual behavior of the digital-self unit is jointly produced by five devices and reserved as a step in the unit. One simulation step in the Crowd Intelligence Network Model is called a generation. The state set of one digital-self in the generation series is described as a path in the pattern.

A pattern is an abstract representation of all possible states set in all generations. It is described by the directed acyclic graph in generation series; the arc indicates the behavior, and the node indicates the individual state in the scene. The simulation pattern is confirmed when the generation size and state transition relationship are defined, indicating that the pattern is already confirmed before the simulation starts. Simulation execution aims to search for a path that conforms to individual intelligence in the simulation pattern based on the time sequence. Individual intelligence is engendered by digital self-endowments and dynamic influences from others.

A connector connects the digital-self units in the Social Network and reflects the physical contact in the epidemic spread scene. In addition, the closeness with neighbors is described by the connecting weights in the Social Network. The virus spreads through physical contact, and the digital-self unit performs state transitions based on the self and neighbor's infection status. Simultaneously, the digital-self unit achieves active observation. The unit influences the self-protection level by observing the self-protection level of neighbors. Furthermore, the new self-protection level will be feedback to the next generation.

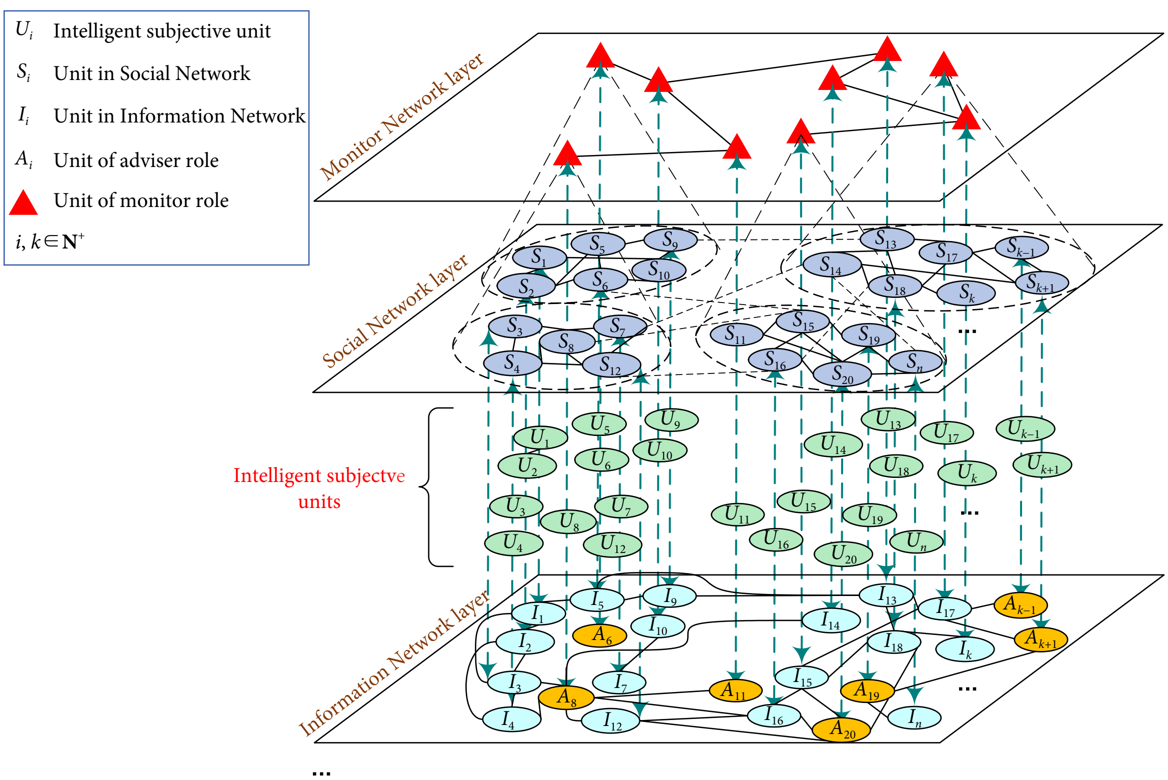

Fig. 3 Crowd Intelligence Network structure.

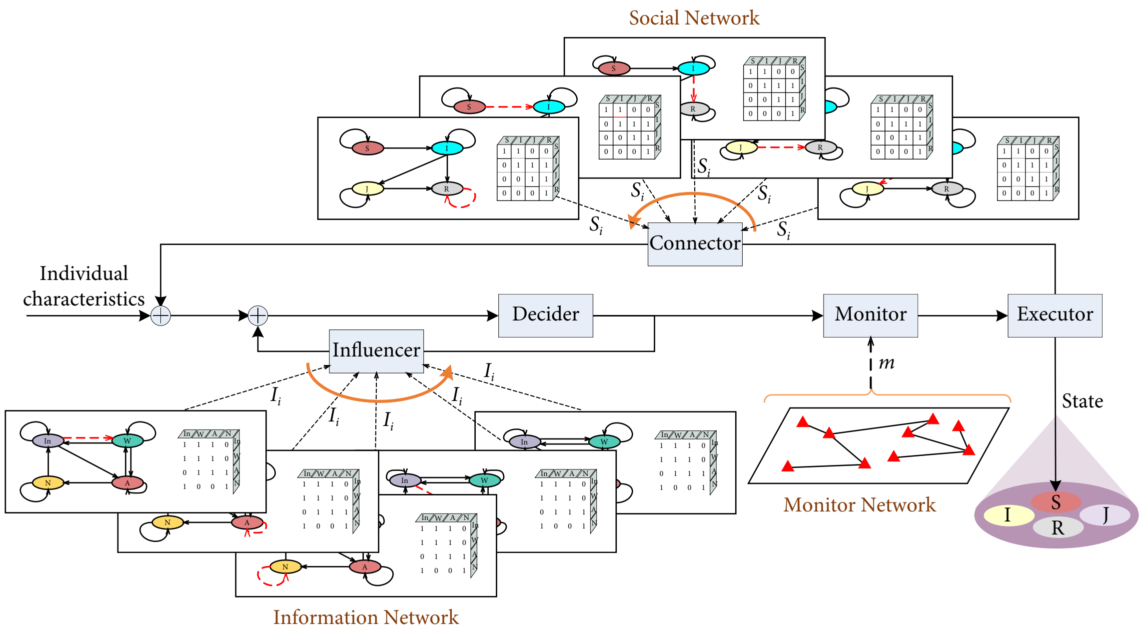

Fig. 4 Digital-self unit structure.

The influencer connects the digital-self units of the Information Network and reflects the unit information interaction in the information dissemination scene. The strength of neighbors is described by the connecting weights in the Information Network. The spread of emotion depends on the information exchange. In addition, the unit converts the new state based on its own and neighbors' emotional state. The adviser is the neighbors who give suggestions to the digital-self unit. The digital-self unit achieves passive influence through the influencer and updates the attitude level based on the adviser influence. Moreover, the new attitude level will continuously feedback to the next generation.

The decider is used to provide an ideal attitude tendency of the digital-self unit. Given the self-regress level of an individual, the attitude of an individual will tend to be uniform with the population. The decider considers the individual endowments and adviser suggestions to provide the individual ideal attitude level tendency.

The monitor is used to describe the external corrected forces of the digital-self unit. In the epidemic monitoring scene, the inspection department supervises the members through the Monitor Network, and the weight of the Monitor Network determines the intensity of external monitoring. In addition, the monitor has a self-discipline level, which represents the unit's ability to maintain its original attitude level.

The executor summarizes the results of other devices and provides the actual infection state of the digital-self unit. Based on the ideal attitude tendency of the decider and the monitoring of the monitor, the executor uses the self-protection level based on the connector observation to calculate the self-protection level. The impact ratio is affected by the self-confidence level. Moreover, the self-protection level affects the infection state transition probability of the digital-self unit in the epidemic spread scene. The digital-self unit will mutate to another state in a small probability to consider the uncertain influence.

3 Member State Transition

The digital-self unit has different state transition relationships in different scenes. Adjacent units influence one another, and state transition is propagated in their respective network layers. The information dissemination scene describes the sensitive state of the digital-self unit to specific information in the Information Network. The epidemic spread scene describes the virus infection state in the Social Network. In addition, the epidemic monitoring scene describes the external corrected forces in the Monitor Network.

3.1 Epidemic spread scene

In the epidemic spread scene, the unit state transition reflects the spread of the virus. The Social Network layer borrows the Susceptible-Infectious-Diagnosed-Recovered (SIJR) model to describe the changes in the infectious status and the spread of the virus. Among them, the S-state unit is easily infected by the infected neighbor. The I-state unit belongs to the infected unit, but it has not been detected. The J-state unit belongs to the infected unit that has been detected. The recovered and dead people are included in the R-state. Therefore, these units will no longer participate in the epidemic spread.

The transformation of the unit's infection state in the Social Network is shown in Fig. 5. The left diagram is the state transition of the digital-self unit. Considering that the state transition of the digital-self unit is a probabilistic event, each state can maintain its past state. It is used as a self-loop representation in the state diagram. In addition, the right matrix is the state transition matrix. "1" indicates that the state can convert; otherwise, "0". The infection state has two states: I and J. The S-state unit may change to I-state when it meets an I-state neighbor. The I-state unit may change to J-state after detection. The infected state unit will change to R-state with a certain probability. The reaction equations of the infection state transition in the epidemic spread scene are as follows:

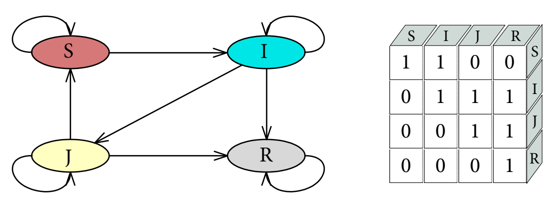

Fig. 5 State transition in the epidemic spread scene.

$$\begin{cases} S(i)+I(j) \xrightarrow{\mu T_i^g} I(i)+I(j), \\ S(i)+J(j) \xrightarrow{T_i^g} J(i)+J(j), \\ I(i) \xrightarrow{\alpha} J(i), \\ I(i) \xrightarrow{\beta_1} R(i), \\ J(i) \xrightarrow{\beta_2} R(i) \end{cases} \tag{1}$$

As shown in reaction Formula (1), i and j describe two contacted units, and $S(i)$ indicates that i is an S-state unit in the Social Network. It is the same for the other three states. The digital-self unit in the S-state will change by T_i^g probability to the corresponding state after contacting the J-state unit. In addition, the converted probability of S-state to I-state is the μ times of S-state to J-state. The I-state unit is converted to J-state after being detected, and the conversion probability is represented by the detection rate α. β_1 represents the removal rate of the I-state unit, and β_2 represents the J-state removal rate. These two parameters affect the unit's removal probability in spread simulation.

3.2 Information dissemination scene

In the information dissemination scene, the state transition of the digital-self unit reflects the dissemination of emotions. The emotion of the current unit is affected by the emotion spread in the Information Network. The emotional state transition of the unit conforms with the Indifference-Worried-Afraid-Numb model (IWAN). The digital self in the In-state shows indifference after receiving the messages of the epidemic. If the digital-self unit is in the W-state, then it is worried about the epidemic spread. The A-state unit shows that the digital-self unit is afraid after receiving messages of the epidemic. However, when several messages of the epidemic are received, the digital-self unit will change to N-state that is numb to the message.

The emotional state transition of the digital-self unit in the Information Network is shown in Fig. 6. The digital-self unit in the In-state has an indifferent attitude toward the epidemic messages, and their attitude level is relatively low. When several units receive the epidemic message, emotions rapidly spread in the Information Network. When the digital-self unit in In-state receives a message from the unit in W-state, the digital-self will change to W-state with a certain probability. The W-state unit will regress when not enough irritating messages are received for a long time. The W-state unit will change to A-state with a certain probability after receiving the message from the A-state unit. Digital-self units in A-state will also degrade to W-state when they do not receive messages from higher emotional state units for a long time. In addition, digital-self units in A-state continue to receive the epidemic information, and then they will change to N-state and become numb to all epidemic information. The unit in the N-state will degrade to the In-state if no epidemic information stimulus is received for a long time.

$$\begin{cases} In(i)+W(j) \xrightarrow{\omega u_i^g} W(i)+W(j), \\ W(i) \xrightarrow{r_i} In(i), \\ In(i)+A(j) \xrightarrow{\omega u_i^g} A(i)+A(j), \\ A(i) \xrightarrow{r_i} W(i), \\ W(i)+A(j) \xrightarrow{\omega u_i^g} A(i)+A(j), \\ A(i)+A(j) \xrightarrow{\omega u_i^g} N(i)+A(j), \\ N(i) \xrightarrow{r_i} In(i) \end{cases} \tag{2}$$

The transition of the emotional state in the information dissemination scene is shown in the reaction Formula (2). Similar to the epidemic spread scene, the variables i and j describe two contact units, and $In(i)$ indicates that unit i is in the In-state. It is the same for the other three states. The W-state or A-state

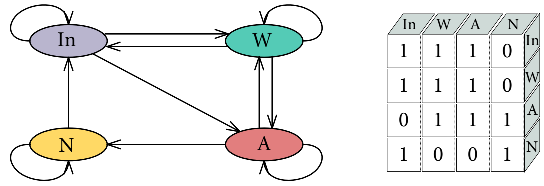

Fig. 6 State transition in the information dissemination scene.

neighbors easily infect the digital-self unit in In-state, and the infection probability is ωu_i^g. u_i^g represents the attitude level, which is a transformation probability adjusted by variable ω. The specific expression of the attitude level is described in Section 6, and it is associated with an individual's characteristics and changes with the current emotional state. The W-state unit exchanges information with the A-state neighbor and the transformation probability is based on ωu_i^g. The W-state unit will regress to In-state when it does not receive enough information stimulus. The regression probability is affected by the self-regress level r_i of the digital-self unit. Similarly, the A-state unit will regress into W-state. A-state unit will become N-state with ωu_i^g probability when it continuously receives the information stimulus. The N-state unit numb with epidemic information will return to In-state with r_i probability when no enough information stimulation is received for a long period.

Furthermore, subtle osmosis effects will occur between digital-self units through the attitude level. Unit's state change will cause the attitude level to increase. The unit attitude level will gradually convert to a higher emotional state after being continuously strengthened. In addition, the degradation of the attitude level primarily causes the reverse transformation of the state.

3.3 Epidemic monitoring scene

The epidemic monitoring scene achieves the global adjustment of the attitude level and self-protection level through a hierarchical network. It does not have the state transition similar to other network layers. In the epidemic monitoring scene, the unit is detected after having evident symptoms. Compared with the R-state, the isolated unit in the I-state still participates in the state transition of the information dissemination scene. The units cannot predict their own infection state; thus, their attitude level will follow up when a unit is infected. It is used to simulate the phenomenon that people's attention to the epidemic suddenly increases after getting sick. The current epidemic inspection system is carried out by provinces and cities in China, and it can regard the inspection system as a tree structure. However, the monitored units have a huge population base. This paper abstracts the monitoring department as the root node of a tree to simplify the simulation calculation. All digital-self units are subject to unified monitoring by the monitoring department with the same monitoring intensity.

4 Simulation Advancement Algorithm

Simulation advancement is based on the Crowd Intelligence Network structure and digital-self model, which is used to achieve the interaction of the digital-self unit in the network and advance the simulation to the next generation.

4.1 Model assumption

In ensuring the model, we make some assumptions to reduce the complexity of the model. First, the simulation of COVID-19 infection in this paper only considers the impact of COVID-19 on population changes. It does not consider the impact of other factors on the population, such as other epidemic diseases spread and natural birth or death. Usually, the natural growth rate of the population is stable. Within the time span of the simulation, the natural birth rate and death rate have little effect on the population.

● In the epidemic spread scene, this paper obtains the following assumptions:

(1) This paper assumes that the Social Network can fully describe the contact relationship of virus spreading. In addition, the SIJR model ignores the increase of contagion risk in the same environment (such as in the same hospital and restaurant).

(2) This model simplifies the infection state of people into four types: S, I, J, and R. It also assumes that these four states can reflect the COVID-19 spread in the Social Network. The patients who die of COVID-19 are found in R-state.

(3) The Social Network weight is stable, and it does not consider the dynamic changes of the network structure. The total number of people in the surveyed provinces is constant. The number of inflow and outflow populations is equal.

● In the information dissemination scene, this paper obtains the following assumptions:

(1) This paper assumes that the Information Network can fully describe the communication relationship under social platforms in the real world. The Information Network weight is stable, and it does not consider the dynamic changes of the network structure.

(2) This paper simplifies the emotional state of people into four types: In, W, A, and N. It also assumes that these four states can reflect the spread of emotions in simulation.

(3) In the IWAN model, the adviser gives advice based on their own experience and endowments. This paper assumes that the message transmission in the digital-self unit is credible, and no false component is found. The impact of false information is handled by introducing random factors.

● In the epidemic monitoring scene, this paper obtains the following assumptions:

(1) The digital-self unit in the Monitor Network is affected by a single monitor. Given the large population base, the size of inspection departments is negligibly relative to the total size of people. The monitor unit as the root node and other digital-self units as leaf nodes present a tree structure of height two. The influence level to the digital-self unit is reflected by the connection weight between the root node and leaf nodes.

(2) The Monitor Network weight is stable, similar to the Information Network and Social Network, and it does not consider the dynamic changes of the network structure.

(3) The quarantined people are completely isolated from the outside world, and they are no longer contagious. Therefore, the quarantined people do not affect the spread of disease (infected or be infected). For some special spread circumstances, this paper is reflected by the random factors of the model.

● In addition, this article makes the following regulation to ensure the execution of the simulation:

(1) The simulation is used to advance generation, and one generation means one day of the actual epidemic.

(2) Except for the initial source of infection, the infection mode of COVID-19 is regarded as contact with patients.

(3) The infection probability is affected by the unit's endowments and neighbor interaction in the Crowd Intelligence Network. It is different from traditional models, i.e., each patient infection probability is a variable value.

4.2 Simulation advancement method

Simulation execution is the simulated algorithm executed on the basis of generation. The simulation result depends on the initial infection source. After statistics, the statistical data will be recorded in an associative array and displayed as the final result of simulation execution.

4.2.1 Simulation execution

Algorithm 1 describes the simulation framework. The simulation goes through M times generation. In addition, the initial generation 0 is added in L_m, which is a set of simulation generation. The multi-layer coupled network structures, namely, Crowd Intelligence Network, use $G = (V, E)$. The Social Network and Information Network are subnets of the Crowd Intelligence Network, and they are separately expressed by $G_s \subseteq G$ and $G_i \subseteq G$, respectively. T_s is used to store the number of individual infected states in each generation of the epidemic spread scene, and T_i is used to store the number of individual emotional states in each generation of the information dissemination scene.

4.2.2 Network expansion algorithm

Algorithm 2 describes the expansion mechanism of intelligence in the network. Each generation of simulation can be regarded as a traversal of an expanded network and the infection state calculation of individuals. However, the infection spread is a dynamically interacting process. Individuals expand the simulation network by active contact. The expanded individual calculates the infection states based on the source state.

In the epidemic spread scene, the infection state is described by s_v. i_v describes the emotional state in the information dissemination scene. These variables are the final statistics data of each generation. In Algorithm 2, *Change_Social_State* and *Change_Information_State* methods are converted on the basis of reaction Formulas (1) and (2) from member state transition. Furthermore, *Change_Social_State* method requires the actual

Algorithm 1 Simulation execution method

Simulation_Execute (L_m, G)

Input: L_m : the simulation number set of $\{0, 1, 2, 3, \ldots, M\}$, including the initial generation
G : the initial graph of simulation

Output: $\langle T_s, T_i \rangle$: T_s and T_i used to store the count number of every state which are organized by generation

$G_s \leftarrow$G //initialize Social Network graph which is waiting for extends
$G_i \leftarrow$G //initialize Information Network graph which is waiting for extends
$n_s \leftarrow 4$ // n_s means the infected state number
$n_l \leftarrow 4$ // n_l means the emotional state number
let T_s be a new $(m+1) \times n_s$ array and make all 0
let T_i be a new $(m+1) \times n_l$ array and make all 0
foreach t in L_m do
  foreach v in $G.V$ do
    $S_m \leftarrow v$'s neighbor in G_s
    $I_n \leftarrow v$'s neighbor in G_i
    $\langle s_v, i_v \rangle \leftarrow$ *Expansion_Network* (v, S_m, I_n)
    $T_s[t][s_v]$+=1
    $T_i[t][i_v]$ +=1
  end
end
return $\langle T_s, T_i \rangle$

Algorithm 2 Network expansion method

```
Expansion_Network (v, S_m, I_n)
Input:   v: a digital-self object
         S_m: the node's neighbors object list in Social Network and length is m
         I_n: the node's neighbors object list in Information Network and length is n
Output:  s_v : the state code of digital-self in Social Network
         i_v: the state code of digital-self in Information Network
i_v ← Change_Information_State(v.i_o) //the original state code of v in Information Network
u ← Information_Network_Influence(I_n) //attitude level of digital-self to spread information
p ← Social_Network_Influence (u, S_m) //protective level of digital-self to viral infection
s_v ← Change_Social_State(p, v.s_o) //s_o the original state code of v in Social Network
foreach o_j in S_m do //1 ⩽ j ⩽ m
   Add o_j into G_s //extend Social Network graph
   if o_j.s_o is Null or s_v is the higher state of o_j.s_o then
      o_j.s_o ←s_v
   end if
end
foreach o_j in I_n do // 1⩽ j ⩽ n
   Add o_j into G_i //extend information network graph
   if o_j.u ⩾ u then // v is only affected by neighbors whose attitude level is higher than himself
      if o_j.i_o is Null or i_v is the higher state of o_j.i_o then
         o_j.i_o ←i_v
      end if
   end if
end
return s_v, i_v
```

transformation probability T_i^g, which is obtained by p. Notably, T_i^g only describes a statistically probabilistic event, and two cases are found in actual state transitions: probable transformation or maintained current state. However, p is calculated using the *Information_Network_Influence* and *Social_Network_Influence* methods. The next section will use the recursive formula to elaborate the calculated method of p and clearly describe the relationship among u, p, and T_i^g.

5 Calculation of Transformation Probability

The self-protection level p is jointly affected by the information dissemination scene, epidemic spread scene, and epidemic monitoring scene. The information dissemination scene simulates the emotional states of the epidemic information, which are quantized by the attitude level, and the higher the attitude level, the stronger the self-protection awareness. The epidemic spread scene simulates the spread of the epidemic, and individuals' protection capabilities to the virus are quantized by the self-protection level. Similar to the information dissemination scene, the higher the self-protection level of the digital-self unit, the lower the probability of the infecting virus. The epidemic monitoring scene simulates the external monitoring force of the real world, which can be macro-regulated on the development of the epidemic. The researchers can directly affect the self-protection level of the digital-self unit by changing the monitoring strength and indirectly affect the infection probability by adjusting the attitude level of the digital-self unit in a particular generation.

Here, this simulation defines the number of units as N and the simulation generation as M. $i \in ID$ represents an individual in the simulation, where $ID = \{0, 1, 2, 3, \ldots, N-1\}$ is the unit's identity set.

Unit's attitude to the epidemic determines the self-protection level. During simulation execution, the self-protection level is jointly affected by many factors. Therefore, based on different influencing factors of the self-protection level, we divided the self-protection level into three stages, namely, ideal stage, self-regress stage, and final stage, which are represented by $p_i^{g'}$, $p_i^{g''}$, and p_i^g, respectively. The final self-protection level of the digital-self unit is generated through the process of the ideal stage and self-regress stage.

Every unit has an initial attitude level before the simulation start, which is defined as u_i^0. It follows normal distribution at the beginning. The digital-self unit must generate p_i^0 based on u_i^0 when initializing. The conversion relationship between the initial attitude level u_i^0 and actual self-protection level p_i^0 is shown in Eq. (3).

$$p_i^0 = \log\left(u_i^0\right) \tag{3}$$

Except for the initial attitude level u_i^0, the attitude level of a new generation is calculated by aggregating advisers' attitude level of the previous generation. It reflects the passive learning ability of the digital-self unit, and the self-confidence level regulates the impact proportion of advisers.

$$u_i^g = f_i u_i^{g-1} + \frac{(1-f_i)\sum\limits_{j \in R_i^I}\left(I_{ij} u_j^{g-1}\right)}{\sum\limits_{j \in R_i^I} I_{ij}} \tag{4}$$

Equation (4) describes the calculation of the individual attitude level by the influencer. u_i^g represents the attitude level of the i unit in $g \in \{1, 2, 3, \ldots, M\}$ generation. f_i is known as the self-confidence level, which is one of the unit's endowments. It describes the unit's persistence degree of its own opinions. The digital-self unit adjusts the attitude level through f_i. The higher the self-confidence level unit, the higher the proportion of the past generation in the current generation attitude level. R_i^I is the adviser set of unit i in the Information Network. The neighbor whose attitude level is higher than i used j to express $j \in R_i^I$. The weight of unit i and unit j in the Information Network is recorded as I_{ij}, and it identifies the credibility of the suggestion. High weight indicates more recognition of the digital-self unit to the adviser suggestion. After receiving advisers' suggestions, the digital-self unit will change to the corresponding emotional state based on the transition rules of the emotional state.

The ideal self-protection level of unit i in the g generation is defined as $p_i^{g'}$, $g \in \{1, 2, 3, \ldots, M\}$. Equation (5) describes the Logarithmic transformation relationship between attitude level u_i^g and the ideal self-protection level $p_i^{g'}$. The ideal self-protection level will increase with the growth of the attitude level. The growth rate of the self-protection level will slow down with the improvement of attitude level.

$$p_i^{g'} = \log\left(u_i^g\right) \tag{5}$$

The self-protection level after regression is represented by $p_i^{g''}$. It will regress to ideal self-protection, and the regressed proportion is adjusted by the self-regress level.

$$p_i^{g''} = (1 - r_i)p_i^{g'} + r_i p_i^{g-1} \tag{6}$$

Equation (6) describes the regression mechanism of the self-protection level. r_i indicates the self-regress level of unit i, and it is an endowment of the digital-self unit. It describes that the unit deviates degree from the past self-protection level. The higher the self-regress level unit, the lower the proportion of the past self-protection level that influences the current generation.

p_i^g represents the final self-protection level of unit i in the g generation and reflects the active observation ability of the digital-self unit. The self-protection level of the new generation is generated by aggregating the protective behavior of neighbors, and the influence ratio of neighbors is regulated by the self-discipline level.

$$p_i^g = d_i p_i^{g''} + \frac{(1-d_i)\sum_{j \in R_i^S} \left(S_{ij} p_j^{g-1}\right)}{\sum_{j \in R_i^S} S_{ij}} \tag{7}$$

Equation (7) describes the calculation method of the final self-protection level. d_i indicates the self-discipline level of the digital-self unit, and it is one of the endowments of the digital-self unit. It describes the ability to maintain own behavior, and the higher the self-discipline level of the unit, the lesser the proportion of neighbors that affects the unit's behavior. R_i^S is the observed neighbor set of unit i in the Social Network, and $j \in R_i^S$. The weight of units i to j at the Social Network is described as S_{ij}. It identifies the closeness between the digital-self unit and the observed neighbor. The closer the relationship, the higher proportion of unit acknowledges to observe neighbor behavior.

After calculating the real self-protection level, the executor normalizes the result to obtain the protection rate P_i based on Eq. (8).

$$P_i = \frac{p_i^g - p_{min}}{p_{max} - p_{min}} \tag{8}$$

In the epidemic monitoring scene, the digital-self unit is supervised by a monitor. The monitor uses a unified influencing factor, $m \in (0,1)$, to control the unit's state transition probability. In addition, ϕ is proportional coefficients used to control the transition probability within a reasonable value range. The calculation of the temporary state transition probability $T_i^{g'}$ is shown in Eq. (9). As shown in Eq. (10), if the range of $T_i^{g'}$ exceeds the limit, then $T_i^g \in [0,1]$ will take the boundary value.

$$T_i^{g'} = \phi(1 - mP_i) \tag{9}$$

$$T_i^g = \begin{cases} 0, & T_i^{g'} < 0; \\ 1, & T_i^{'} > 1; \\ T_i^{g'}, & 0 \leqslant T_i^{g'} \leqslant 1 \end{cases} \tag{10}$$

The monitor can influence the state transition probability not only by using m but also by changing the unit self-protection level. The influencing mechanism is shown as follows:

$$u_i^{g'} = \begin{cases} u_i^g + \gamma\left(u_{max} - u_i^g\right), & 0 \leqslant \gamma \leqslant 1; \\ (1+\gamma)\, u_i^g, & -1 \leqslant \gamma < 0 \end{cases} \tag{11}$$

Equation (11) indirectly affects the state transition probability by changing the unit's attitude level in the specified generation. $\gamma \in [-1,1]$ is the factor influencing attitude. It inhibits the unit's self-protection level when $-1 \leqslant \gamma < 0$. In addition, unit's attitude level is reduced by $1+\gamma$ times of the original attitude level. γ will promote unit's self-protection level when $0 \leqslant \gamma \leqslant 1$. Moreover, unit's attitude level is increased γ times of the difference between the max limit of the attitude level and the current attitude level. However, the growth is limited by the maximum value of the attitude level, and the growth gradually slows down, which is consistent with actual life experience. The modified attitude level directly affects the self-protection level of the next generation and indirectly affects the transfer probability of the digital-self unit.

6 Simulation Analysis

This section simulates the outbreak of COVID-19 epidemic. The COVID-19 epidemic data are counted by King[41]. In addition, it is the news published by the National Health Commission of the People's Republic of China[42]. The construction of the Social Network is based on the Friendster dataset, which has ground-truth communities[43]. Moreover, the Information Network is a Small-world Network, which has five nearest neighbors in a ring topology and a 0.1 probability of rewiring each edge[44]. The parameters of the epidemic spread simulation in the free simulation are shown in Table 1.

Based on the parameter setting shown in Table 1, the infection trend under the free simulation is shown in Fig. 7. However, the deviation between the existing confirmed cases and the simulation data began on January 23, 2020.

At the inflection point, the number of confirmed cases under free simulation is larger than the statistical cases. The simulation curve still declines even without monitoring. The simulation curve of the Information Network layer is shown in Fig. 8. Considering the number of digital-self units changing to W- or A-state, the self-protection level of the digital-self unit increases simultaneously. Thus, it reduces the state transition probability at the Social Network layer, and curbs the proliferate trend of the epidemic spread. However, with the information spread of the epidemic, several digital-self units are gradually changing from W- or A-state to N-state. The virus spreads at a relatively high level of protection and reduces infection rates.

According to the Notice of the Hubei People's Government, Wuhan City was locked down at 10 o'clock on January 23, 2020[48], and the overall trend of the epidemic was intervened by external monitoring. Therefore, in simulating the intervention, m is set higher to adjust the infection trend on January 23, 2020.

The comparison between the adjusted simulation and the actual statistical result is shown in Fig. 9. However, after the impact of the monitoring level, the inflection point of the simulation has a 2 to 3 days deviation from the inflection point of the statistics, but the simulation trend is fitted with the historical statistics of Wuhan. Notably, the monitoring level directly affects the infection probability of the digital-self unit. With the increase of the monitoring level, the infection probability is decreased.

Table 1 Parameter values for the model.

Simulation scene	Parameter	Value/range
Epidemic spread scene	μ	0.55[45]
	α	0.321[46]
	β_1	0.04–0.1[47]
	β_2	0.04–0.1[47]
Information dissemination scene	ω	1–2
Epidemic monitoring scene	ϕ	0–1
	m	1–2

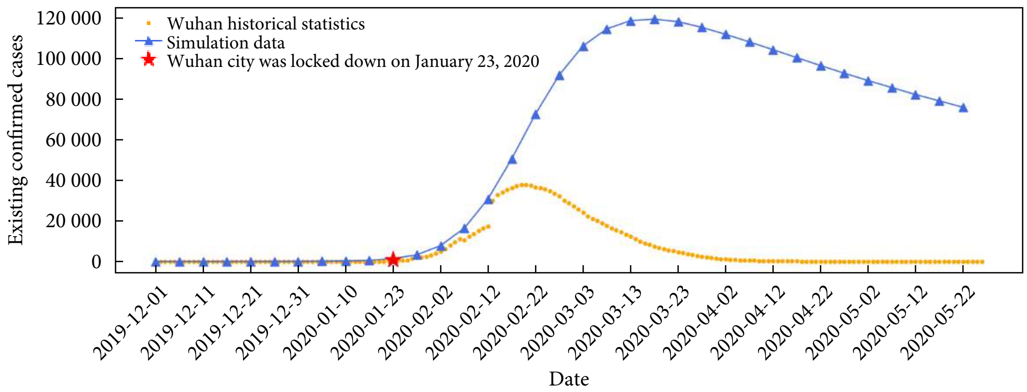

Fig. 7 Comparison between free simulation and historical statistics of Wuhan.

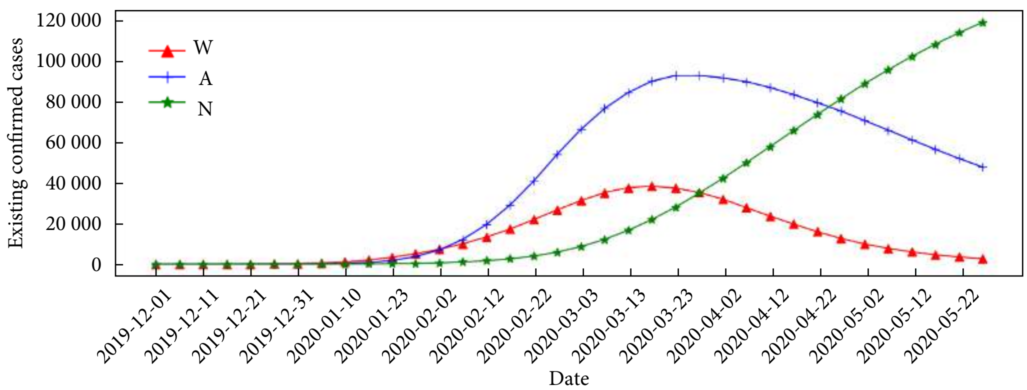

Fig. 8 Simulation trend of emotional state.

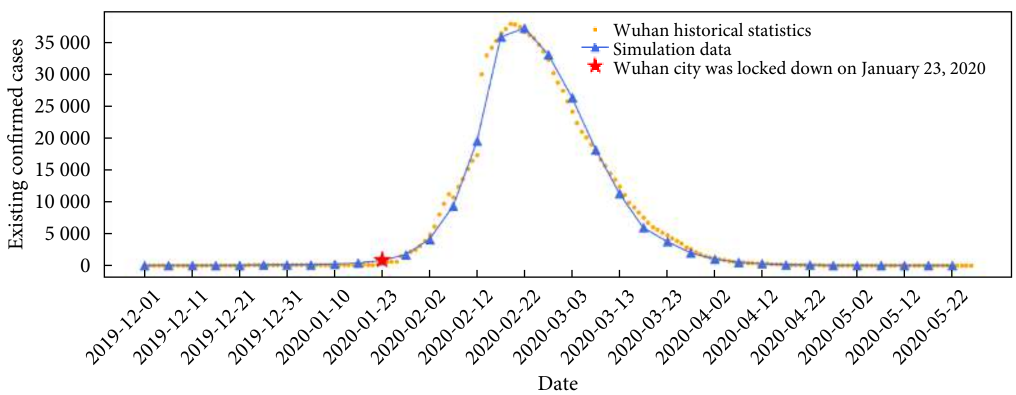

Fig. 9 Simulation trend after adjustment.

Therefore, the isolation strategy (curb population flow and travel restrictions) has an important effect on the overall development of the epidemic.

In the beginning, with the changes of emotional state, several digital-self units are in A-state. The level of protection of an infected person is increasing, thereby reducing the virus' infection rate. However, several units are converted to N-state; thus, the protection level of digital-self tends to be stable, and the degree of impact decreases.

7 Conclusion

This paper applies the Crowd Intelligence Network Model to study the epidemic spread mechanism and discuss the epidemic spread in the multiple-scene intervention. Compared with the macro model, the Crowd Intelligence Network Model can add individual characteristics with different distributions, which easily reflects personal individuality. Compared with the Cellular Automata Model, the Crowd Intelligence Network Model uses the complex network to describe the relationship between simulation members, which flexibly describes the real world complex relationship. In addition, compared with the Multi-agent Model, the Crowd Intelligence Network Model achieves the joint interaction of multiple scenes, which discusses the crossover impact of different factors under multiple scenes, such as an environmental factor. Therefore, the Crowd Intelligence Network Model has advantages in simulation research that needs individual characteristics, complex relationships, and multi-scene interactions.

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