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Research Article

An Epidemic Spreading Simulation and Emergency Management Based on System Dynamics: A Case Study of China's University Community

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The spread of epidemics, especially COVID-19, is having a significant impact on the world. If an epidemic is not properly controlled at the beginning, it is likely to spread rapidly and widely through the coexistence relationship between natural and social systems. A university community is a special, micro-self-organized social system that is densely populated. However, university authorities in such an environment seem to be less cautious in the defence of an epidemic. Currently, there is almost no quantitative research on epidemic spreading and response strategies in universities. In this paper, a case study of a university community is considered for a simulation of an infection evolving after an epidemic outbreak based on the method of system dynamics of the three stages. The results show the following: (1) By improving the speed of the initial emergency response, the total number of patients can be effectively controlled. (2) A quarantine policy helps to slow down the evolution of infection. The higher the isolation ratio, the higher the cost; therefore, the isolation ratio should be optimized. (3) It is important to make emergency plans for controlling epidemic spreading and carry out emergency drills and assessments regularly. According to the results of this study, we suggest an emergency management framework for public health events in university communities.

1. Introduction

In the 21st century, the world has suffered from frequent public health emergencies, such as SARS, H1N1, H7N9 avian influenza, dengue fever, and coronavirus disease 2019 (COVID-19). In particular, the rapid epidemic spread and wide range of infections from COVID-19 have seriously threatened people's lives and health, disrupted social life and production order, and affected the development of the world economy [1]. In the face of a sudden pandemic, the public is ill-prepared to prevent infection, particularly in densely populated and self-organized social systems such as university communities. Universities are the frontlines for talent training, scientific research, and technological innovation. Therefore, safety and stability are important foundations for the self-management of universities and are also key factors for national development and social stability [2]. Previous research has shown that many university authorities did not take emergency response management seriously [3], which has led to deficiencies in emergency response capabilities, especially in the field of public health event prevention. For the reasons above, it is important for the university authorities to construct an effective emergency response management system on the basis of which to improve the effectiveness of prevention and control of public health events.

In China, the COVID-19 outbreak occurred during a winter vacation, and most students had returned home safely. Although it did not cause large-scale infection on campus, it inevitably disturbed routine teaching plans and academic exchanges. It should be noted that there are a number of people in university communities, and in the event of a public health outbreak, the consequences are unpredictable. COVID-19 is undoubtedly among the few viruses that are extremely harmful, widespread, and have a long impact duration in the world. Due to various internal and external influences, the evolution of an infection is often complex and has uncertain consequences, and it is difficult to describe the process by using regular experimental methods, which makes it hard to provide experimental reference for subsequent decisions. Therefore, a systematic model of evolution is needed for simulation and to find the way of epidemic prevention and control in the future.

Since the outbreak of COVID-19, researchers have given considerable attention to emergency management issues. The main purpose of this research is to achieve policy optimization. However, among which, a qualitative analysis does not go beyond the previous policy framework, and a quantitative analysis does not reveal the full picture of evolutionary mechanisms either. Therefore, in order to predict the evolutionary trend and scope of impact of an event promptly and provide effective methods to control epidemic spread, there is a need to use COVID-19 as an object to study the basic prevention policies and control systems based on the simulation of epidemic evolution. In this study, we assume that a university community in China is affected by the epidemic and adopt a system dynamics methodology to simulate the three stages after an epidemic outbreak, then observe the number of infections and the epidemic spreading process to learn the feedback mechanism of infection. As compared with traditional mathematical modeling and simulation, the result is much closer to the real, evolving circumstances. A model based on system dynamics also provides useful tools for decision-makers to learn, analyze, and efficiently respond to future public health events. As compared with a general qualitative analysis, the countermeasures of this study are more logical and persuasive.

2. Literature Review

2.1. Emergency Management. Emergency management mainly deals with emergencies such as natural disasters, accidents, public health events, and social security incidents [4]. Modern emergency management was started in western developed countries, such as the establishment of the Federal Emergency Management Agency of the United States in 1979, which marked the formal establishment of a modern emergency management mechanism in the United States [5]. Since then, countries have begun to study the basic issues of modern emergency management, which mainly include two categories.

The first issue concerns the public health emergency management system. Sang and Brower discussed the gap between the formal plans of the US local government emergency services and actual networks, and provided a simplified network analysis process to assist decision-makers in planning effective emergency activities [6]. Brand et al. developed a six-step model to improve the emergency response ability of public health agencies [7]. Jenine et al. investigated the coordination ability between personnel of Missouri's public health emergency plan system and related agencies [8]. Asch et al. reviewed and assessed the preparations of California's local public health departments to respond to health threats such as bioterrorism and found significant differences among different tools [9]. Manley et al. used the survey method to quantitatively describe the experience of emergency departments in rural hospitals in the United States in dealing with emergencies and made it clear that preparation activities were helpful in improving the hospital's response capacity [10]. Ha et al. investigated the role of South Korean rural community organizations in local emergency management and their effective coping methods [11].

The second issue concerns the research on emergency resource management, ability training, and personnel evacuation. Larson discussed the resource allocations of police, fire, emergency medical, and other spatially distributed emergency service systems [12]. Bianchi and Church used the coverage model to investigate the positioning of emergency services in ambulances and firefighting systems [13]. Sundaramoorthi et al. used a data integration simulation model to evaluate the nurse-patient configuration of a hospital in Northeast Texas [14]. Nezir developed a two-stage stochastic model and considered the number and locations of field hospitals in order to effectively deal with large-scale disasters [15]. Lucchese et al. established a hybrid model to minimize the cost of medical supply chains, which was verified by the distribution of medical supplies in Apulia, Italy [16].

2.2. Models of Epidemic Spreading. There are two main types of research methodologies on models of epidemic spreading. The first method is to establish a mathematical model for theoretical analysis. Lloyd established an ordinary differential equation system for the spread of diseases [17]. Ball further added randomness to develop a stochastic model [18]; Lipsitch et al. and Riley et al. used this type of stochastic model to analyze the spread of SARS in Singapore and Hong Kong [19, 20]. However, a stochastic model is limited by the defects in the data and the model itself. Subsequently, Xu et al. used the "scale-free network model" to discuss how infectious disease outbreaks were affected by the tendency of geographic links and proved that this model could be used to effectively study the spread and prevalence of infectious diseases based on social contact networks [21]. Salathe et al. focused on the spread of diseases in social contact networks [22]. These models mentioned above can partially reproduce the nature of social contact networks, but it is difficult to satisfactorily show the significant behavioral heterogeneity of different risk groups.

The second method is to use the simulation methodology. Leslie and Brunham used a box model to simulate the spread of AIDS [23]. Fuentes and Kuperman established a homogeneous individual CA model using a cellular automata approach based on a classic dynamics model of traditional diseases [24]. Eubank developed an urban epidemic simulation system that relied on empirical estimates of social networks or contact patterns that were produced by TRAN-SIMS [25]. Subsequently, more and more scholars have paid attention to the application of simulation methodology in the field of public health, such as the simulation of the SARS epidemic process. Some scholars have also explored policy simulation decision support systems. Harper and Shahani used a simulation model to predict the number of AIDS patients and medical expenses in Mumbai, India, which helped to provide effective care for AIDS patients in Mumbai [26]. Lee et al. developed a simulation and decision support system for planning large emergency dispensing clinics that responded to biological threats and infectious disease outbreaks [27]. Mohamed considered the data from the emergency department of a private hospital in Zagazig, Egypt, and proposed a discrete event simulation model, which showed that patients' wait and hospitalization times could be significantly improved [28]. But the simulation methodologies above did not consider the feedback mechanism. Therefore, they were unable to completely reveal the network relationships in the infection evolving.

3. Introduction of Basic Models

3.1. Traditional Infectious Disease Model. The traditional infectious disease model is the compartment model, which is also called the susceptible-infected-recovered (SIR) model. The SIR model was originally proposed by Kermack and Mckendrick in 1927 and has also been called the Kermack–Mckendrick model [29]. It is the earliest and most classic mathematical model used to study infectious diseases. The SIR model (Figure 1) describes the number of people in three different infection states when time changes, namely: susceptible, infected, and recovered. This model assumes that the total population is fixed and does not take into consideration changes in the population due to other diseases or other natural causes of death, and the population does not differ in age and demographic structure. The incubation period of the disease is fixed and does not change over time, and patients who recover from infection are not reinfected (J, Zou) [30].

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} = -\beta I(t)S(t), \tag{1}$$

$$\frac{\mathrm{d}I(t)}{\mathrm{d}t} = \beta I(t)S(t) - \gamma I(t), \tag{2}$$

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = \gamma I(t), \tag{3}$$

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} + \frac{\mathrm{d}I(t)}{\mathrm{d}t} + \frac{\mathrm{d}R(t)}{\mathrm{d}t} = 0, \tag{4}$$

$$N(t) = S(t) + I(t) + R(t), \tag{5}$$

$$R_0 = \frac{\beta}{\gamma}, \tag{6}$$

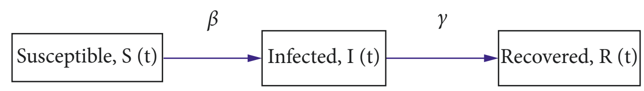


Figure 1: The SIR model.

$S(t)$ represents the group that is susceptible to infection, $I(t)$ represents the infected group $R(t)$, which represents the recovered group , $N(t)$ represents the total group of population in the system, β is the contact rate, γ is the recovery rate, and R_0 is the basic reproduction number.

Equations (1), (2), and (3) represent the instantaneous spreading velocity between the chambers. Equation (4) represents the flow conservation in the system. The R_0 (basic reproduction number) in equation (6) is derived from the SIR model, which includes β (contact rate) and γ (recovery rate) as the two main parameters. In epidemiology, R_0 is often used to measure the dynamics of disease transmission and is the average number of secondary cases caused by an initial onset in a population without immunity. When $R_0 > 1$, the disease will continue to spread in the crowd and the diseasefree equilibrium in the system is unstable; if $R_0 < 1$, the result is the opposite (Dreessche and Watmough) [31]. The SIR model based on the differential equation system can fit the curve more accurately according to the existing data and can use the phase trajectory analysis to obtain the measures to prevent epidemic spread, and the theoretical basis is sufficient.

However, the SIR model is not detailed enough for the classification of a population, especially when the quarantine factor is not explicitly considered. In practice, quarantining suspected patients is an effective way to control epidemic spread. The model does not introduce a feedback mechanism, which inevitably reduces its accuracy if it is only based on existing data for predicting situations in the future. Because quarantine practices or recovered factors are not present in previous data, it is difficult to identify the impact of these factors on epidemic control, which means that, due to the lack of a feedback mechanism, a traditional model is unable to help the system achieve the function of self-adjustment. In this study, the feedback mechanism of system dynamics is more suitable for describing the possible situations of epidemic spread.

3.2. System Dynamics Model. System dynamics (SD) modeling was first proposed in 1956 by Forrester, a professor at the Massachusetts Institute of Technology in the United States. It was originally used to analyze the system simulation method of production management and inventory management, and then it was applied in many fields. System dynamics refers to the behavior of the system as determined by the information feedback mechanism within the system. This model analyzes the structure, behavior, and causality of the system, simulates the dynamic changes of the system, establishes a structural model, and then performs computer simulation operations under different assumptions to predict the dynamics of the system's behavior under various conditions. Classic system dynamic model is wild boar population model (Figure 2).

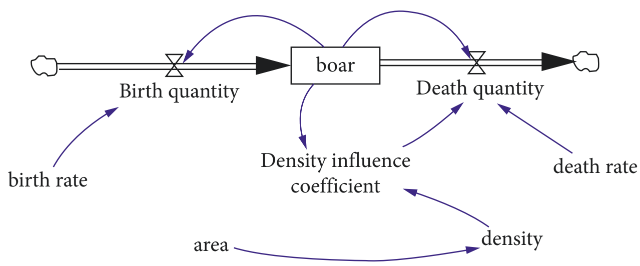


Figure 2: Feedback diagram of a system dynamics model of a wild boar population.

System dynamics modeling can also be used to solve public health problems with complex dynamics. It can represent a society affected by multiple interactions of disease risk, a diseased population, prevention, and control policies. Since 1970, system dynamics models have been applied to many public health problems (Homer and Hirsch) [32], which have included: (1) heart disease, diabetes, AIDS, and cervical cancer; (2) drug abuse, including heroin, methamphetamine, and smoking cessation; (3) emergency medical systems in cases of natural disasters or terrorist acts; (4) organizational planning of population-based health maintenance such as dental care and mental health; and (5) public health issues and epidemiological research. Regarding the study of infectious diseases, food, and other public health problems, system dynamics models can simulate conditions that may occur for certain variables that may affect the overall behavior of the system, can describe problems caused by different policies or without previous data, and can predict what might happen in the future, thus, helping to find an effective solution.

4. Modeling and Simulation

Since the university community is a densely populated place, in the early stages of an epidemic spreading, the reasonable decision is to close campus to isolate the university community from outside contacts and to prevent students from going outside the campuses to reduce the infection rate. Close contacts should be quarantined in a centralized place or in rooms to effectively reduce the crossinfection rate. For this study, we chose a university community that was not infected by the infection evolving simulation. In the closed environment of university communities, when an infection case is found, each stage of simulation prediction is shown a changes in the number of infected, susceptible, and confirmed numbers in the university community in the next step. The analysis of each stage is also based on the initial state, rather than a continuation of the previous state.

For this study, we will take a university in China as an example, which accommodates a total of 6743 teachers and resident students. For the infection evolving simulation, we assumed that a student had been infected with an infectious disease. Modeling with system dynamics methodology, the Vensim PLE8.1.0 operating software was selected for the simulation analysis. By the way, due to the characteristics of the system dynamics methodology, we define the simulation parameters of each stage below, like “FINAL TIME,” “TIME STEP,” and “Contact rate,” etc., according to actual circumstances and specific modeling needs. Therefore, there are no fixed rules or patterns for parameter settings; the main purpose is to observe the evolutionary trends based on these chosen parameters.

4.1. The First Stage

4.1.1. Logical Frame Diagram. In this study, for the analysis of the simulation model, we refer to the university as a school. First, we confirm whether or not there is an emergency response plan for public health events. If the answer is no, we collect as much information as possible and identify what resources can be used to effectively control an infectious disease. The school is a micro-self-organized social system in society. Therefore, we assume that in the event of an infectious disease, the school must be closed. If there were no interventions in the public health event, the spread of disease would have been extremely rapid. We construct a logical framework diagram based on system dynamics theory (Figure 3).

4.1.2. Simulation Parameter Settings

(01) FINAL TIME = 2.5 (unit, week);

(02) INITIAL TIME = 0 (unit, week);

(03) TIME STEP = 0.0625 (unit, week [0, ?]);

(04) Infected people = total number of patients ∗ uninfected ∗ contact rate ∗ exposure to sickness ratio (unit, person/week);

(05) Total number in school = 6743 (unit, person);

(06) Exposure to sickness ratio = 0.012 (unit, 1/person);

(07) Contact rate = 0.1 (unit, 1/week);

(08) Uninfected = total number in school – total number of patients (unit, person);

(09) Total number of patients = INTEG (infected people, 1) (unit, person).

Among them, the “infected people” is the flow in the model, and the “total number of patients” is the stock in the model. The “contact rate” indicates that the probability of a person being in contact with others is 10% each day, and the “exposure to sickness ratio” indicates that with each contact with a patient, there is a 1.2% probability that an uninfected person will be infected.

4.1.3. Infection Evolving Simulation. Each variable in the system dynamics model can be assigned a dimension. In the computing process, it is necessary to test whether the dimensions in the logical framework diagram are consistent. Therefore, after the model is completely built and assigned to each variable, a dimensional consistency test is performed. If “units are OK” is displayed, it indicates that the model passed the consistency test, which means that the units of all dimensions in the model are reasonable. The simulation results of the model are shown in Figure 4.

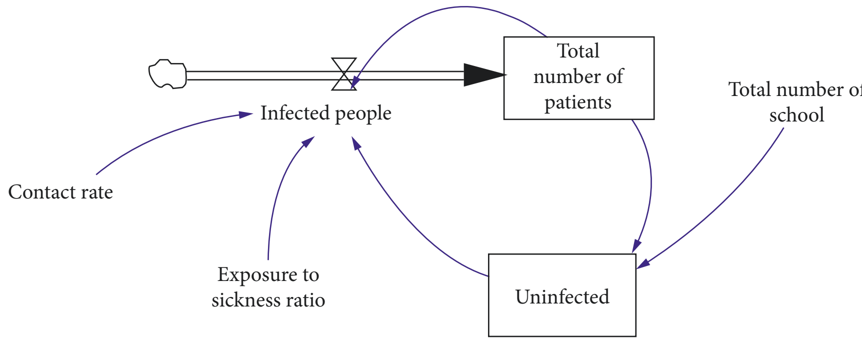


Figure 3: Logical framework diagram of an infection in the first stage.

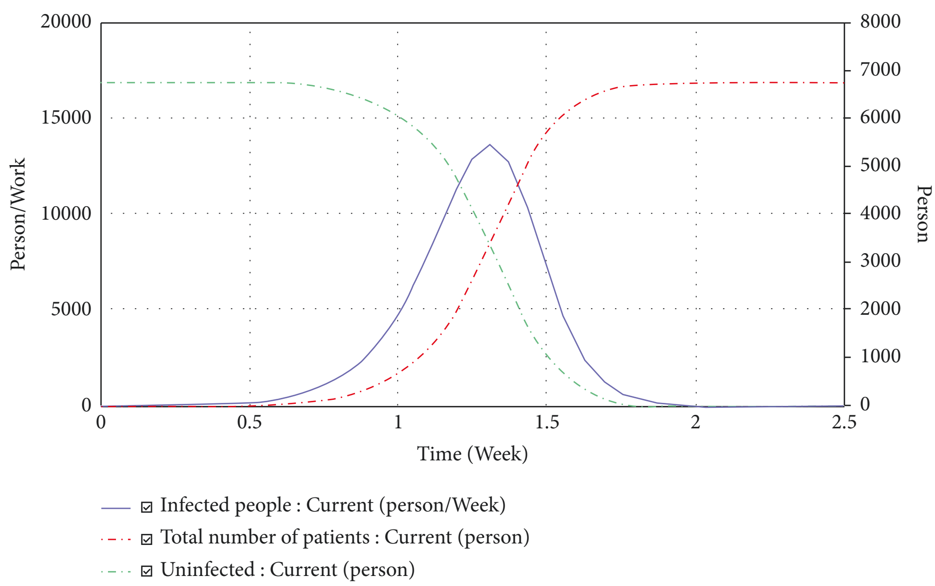


Figure 4: Simulation results of an infection evolving in the first stage.

The simulation results show that the number of "infected people" reaches a peak value of 12,940 in 1.25 weeks, because "infected people" is the flow in the model, the unit is person/week, and there is a situation of superposition. The number of "uninfected" reaches a minimum at 2.25 weeks, and the "total number of patients" also reaches a maximum at the same time, which means that 6743 students are infected.

4.1.4. What Should Be Done in the First Stage?

(1) If there is no emergency response plan, a plan needs to be formulated for public health events. Considering that a university is a micro-self-organized social system, when an infection happens, it is important to access outside help; therefore, university authorities are expected to immediately report infection information. In the meantime, they must also establish an emergency management center and set up special teams to collect as much infection information as possible, as well as send and receive information in a short period of time.

(2) The beginning of an infection is the critical phase. When the first infected person is identified, reducing public gatherings is important. An effective communication plan and volunteer team should be launched and established to assist professionals to help control the epidemic's spread as soon as possible.

(3) Infection information should be reported to the local center for disease control and prevention (CDCP) in time to help find the source of infection. Medical teams and equipment should be organized and immediately dispatched. Teachers and students with initial infections should be transferred and treated.

(4) University authorities should prepare for early warning at the right time and information should be released step-by-step that people care about, to reduce people's fears and suspicions.

4.2. The Second Stage. Depending on the specific circumstances of infection, more and more doctors and anti-epidemic personnel will be allocated to help infected students and teachers with restorative treatment.

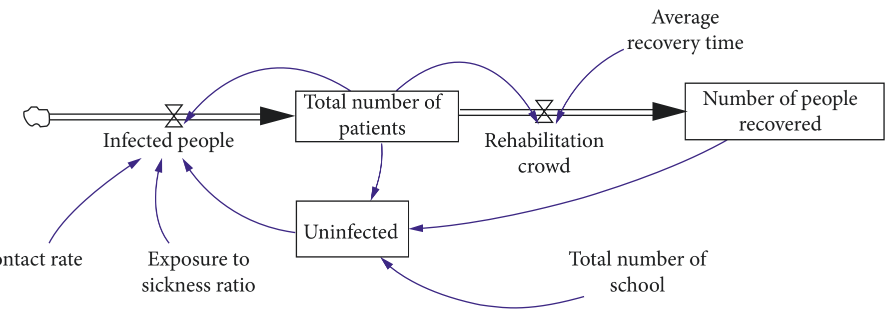


Figure 5: Logical framework diagram of an infection in the second stage.

4.2.1. Logical Frame Diagram. On the basis of the first stage, the number of people who have recovered and the rehabilitation crowd are further considered in the second stage. Then we construct a logical framework for the second stage, as shown in Figure 5.

4.2.2. Simulation Parameter Settings. In order to seek a better simulation effect, the following new variables should be changed/added:

(01) FINAL TIME = 10 (unit, week);

(02) TIME STEP = 0.125 (unit, week [0, ?]);

(03) Number of people recovered = INTEG (rehabilitation crowd, 0), (unit, person);

(04) Average recovery time = 1 (unit, week);

(05) Rehabilitation crowd = total number of patients/average recovery time (units, person/week);

(06) Uninfected = total number in school – number of people recovered – total number of patients (unit, person);

(07) Total number of patients = INTEG (infected people-rehabilitation crowd,1) (unit, person).

Note: (1) among the simulation parameters, the "rehabilitation crowd" and the "infected people" are the flow, while the "total number of patients" and the "number of people recovered" are the stock. (2) Considering the "rehabilitation crowd" and "number of people recovered" were added, parameters "uninfected" and "total number of patients" will change, as demonstrated in (06) and (07).

4.2.3. Infection Evolving Simulation. We perform a dimensional consistency test on the model, and it shows that the units are OK, indicating that the model passed the consistency test. That is, all the dimensional units in the model are reasonable. The simulation results are shown in Figure 6. The number of infected people reaches a peak of 11,511 at 1.625 weeks, as compared with a peak of 12,940 at 1.25 weeks in the first stage, and the "number of people recovered" reaches 6743 in the sixth week. The number of "uninfected" people decreases with an increase in the "number of people recovered". The "total number of patients" reaches a peak of 4596 in the second week and then gradually decreases until the sixth week.

4.2.4. What Should be Done in the Second Stage?

(1) Adjust daily management affairs as needed, including teaching programs, academic exchanges, and some public activities. Meanwhile, some basic measures such as disinfection and ventilation measures should be implemented to keep the campus environment safe.

(2) During the process of preventing and controlling infection, decision-makers and rescuers should hold their positions to ease the pressure and panic of teachers and students, communicate and collaborate with the local CDCP to set up temporary treatment and rehabilitation areas, and prepare temporary quarantine rooms for further use.

(3) An emergency management center should promote a common sense of epidemic prevention on the campus radio and push useful notifications about self-protection, ensure people keep calm and know how to defend against infection by themselves, guide teachers and students to reduce outdoor stays as short as possible.

(4) University authorities should prepare supplies that are needed for epidemic prevention, such as masks and disinfectants, etc., to reduce the possibility of potential risk exposure. In order to prevent further spread, enough food and necessities should be purchased. Volunteers should be prepared to allocate food, medicine, and other supplies to teachers and students in the way of no touch.

4.3. The Third Stage

4.3.1. Logical Frame Diagram. In the third stage, the quarantine factor is considered The number of people quarantined and the recovery rate of infected patients need to be introduced. We construct a logical framework diagram as shown in Figure 7.

4.3.2. Simulation Parameter Settings

(01) FINAL TIME = 8 (unit, week);

(02) INITIAL TIME = 0 (unit, week);

(03) SAVEPER = 0.125 (unit, week [0, ?]);

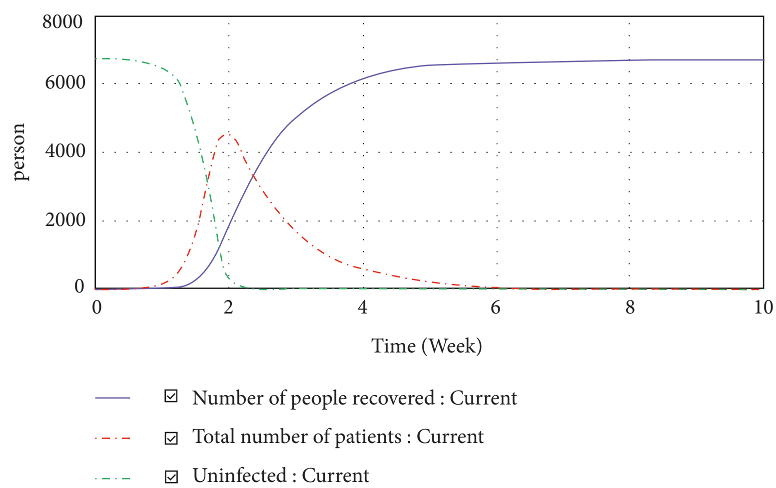


Figure 6: Simulation results of an infection evolving in the second stage.

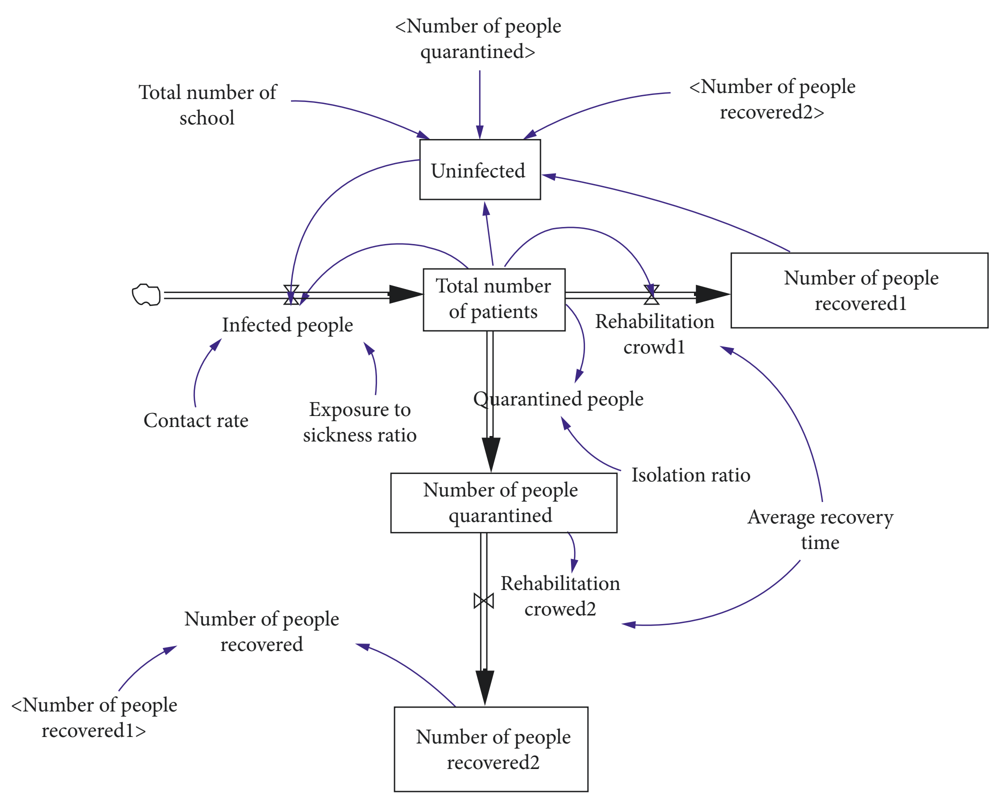


Figure 7: Logical framework diagram of an infection in the third stage.

(04) TIME STEP = 0.125 (unit, week [0, ?]);

(05) Infected people = total number of patients ∗ uninfected ∗ contact rate ∗ exposure to sickness ratio (unit, person/week);

(06) Total number in school = 6743 (unit, person);

(07) Number of people recovered = number of people recovered1 + number of people recovered2 (unit, person);

(08) Number of people recovered1 = INTEG (rehabilitation crowd1, 0) (unit, person);

(09) Number of people recovered2 = INTEG (rehabilitation crowd2, 0) (unit, person);

(10) Number of people quarantined = INTEG (quarantine population - rehabilitation crowd2, 0)(unite, person);

(11) Average recovery time = 1 (unit, week);

(12) Rehabilitation crowd1 = total number of patients/average recovery time (unit, person/week);

(13) Rehabilitation crowd2 = number of people quarantined/average recovery time (unit, person/week);

(14) Exposure to sickness ratio = 0.012 (unit, 1/person);

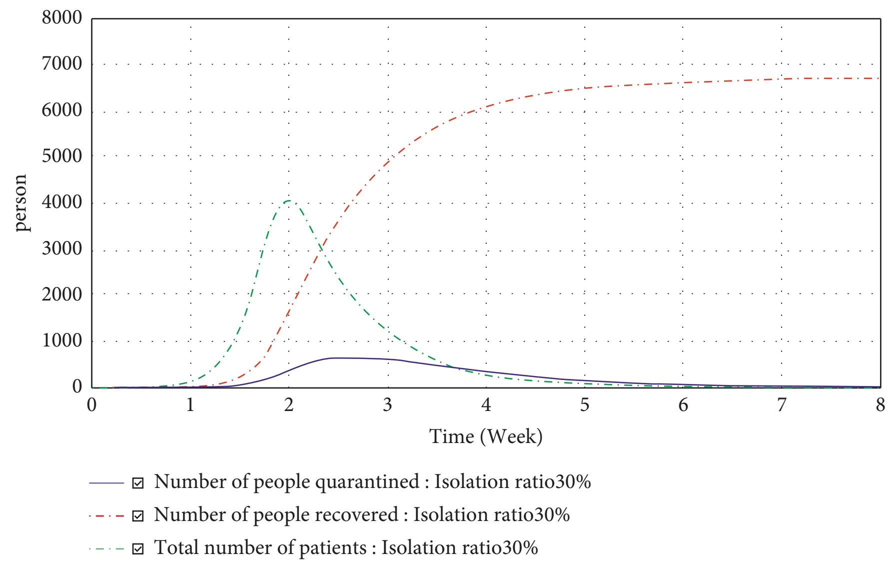


FIGURE 8: Simulation results of an infection evolving in the third stage.

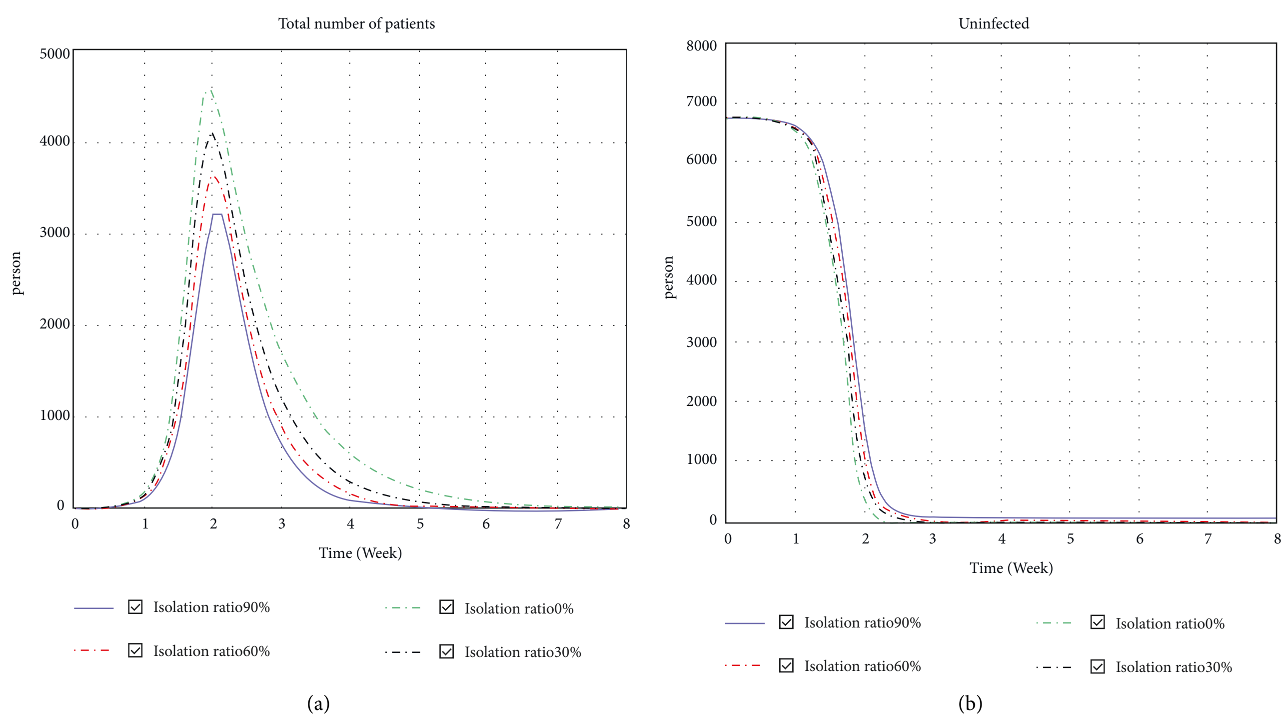
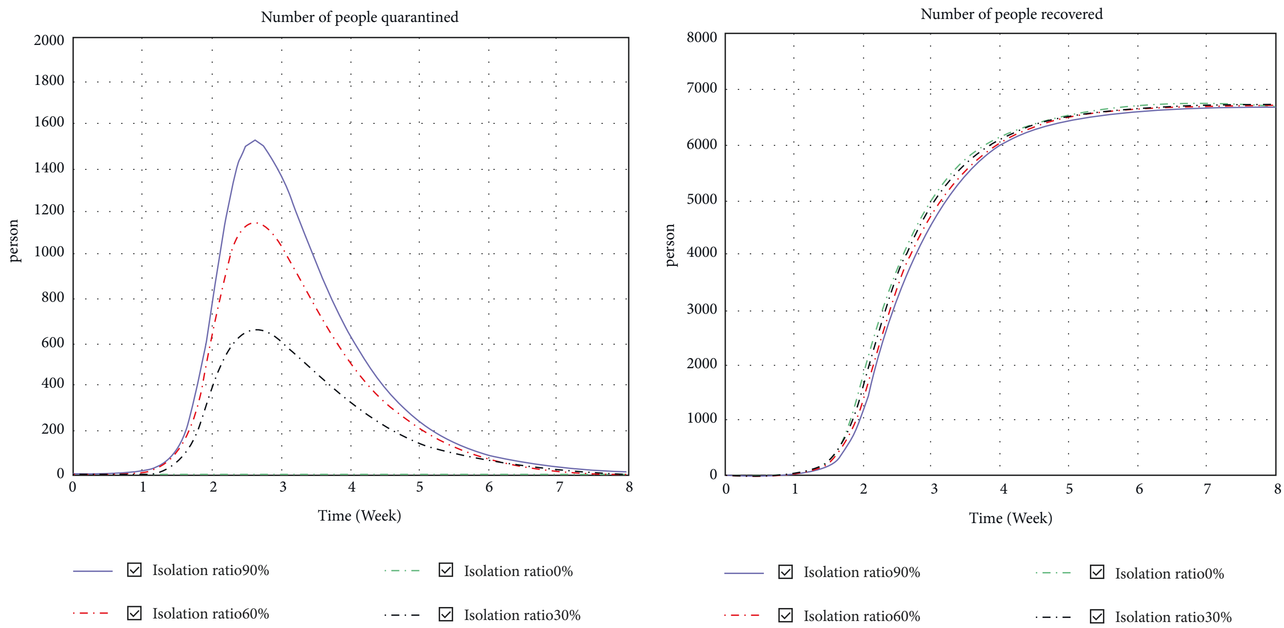


FIGURE 9: Continued.



(c) (d)

FIGURE 9: Simulation prediction results of different quarantine strategies.

(15) Contact rate = 0.1 (unit, 1/week);

(16) Uninfected = total number in school – total number of patients – number of people recovered1 – number of people recovered2 – number of people quarantined (unit, person);

(17) Total number of patients = INTEG (infected people-rehabilitation crowd1 –quarantine people,1) (unit, person);

(18) Quarantine people = total number of patients * isolation ratio (unit, person/week);

(19) Isolation ratio = 0.9 (unit, 1/week);

4.3.3. Infection Evolving Simulation. We perform a dimensional consistency test on the model, and it shows that the units are OK, indicating that the model passed the consistency test. That is, all the dimensional units in the model are reasonable. The simulation results are shown in Figure 8. On the assumption of an isolation ratio of 30%, the “number of people quarantined” reaches a peak of close to 700 at 2.625 weeks, and the “total number of patients” reaches a peak of 4137 at 2.125 weeks. As compared with the second stage, due to the emergence of quarantine, the number of patients at the peak will reduce slightly.

In order to confirm what the optimal isolation ratio will be, we observe the simulation changes of each index as the isolation ratio is adjusted. When the isolation ratio is 0%, the total number of patients reaches a peak of 4596 in the second week. When the isolation ratio is 30%, the total number of patients reaches a peak of 4137 in the second week. When the isolation ratio is 60%, the total number of patients reaches a peak of 3679 in the second week. When the isolation ratio is 90%, the total number of patients reaches a peak of 3211 at week 2.125. It can be seen that, as the isolation ratio gradually increases, the total number of patients reduces accordingly. Other indices of “uninfected,” “number of people quarantined,” and “number of people recovered” are observed, with varying degrees of beneficial change under different isolation ratios as well. However, a quarantine policy is a very expensive solution in the real world, The specific isolation ratio needs to be analyzed in detail if necessary. The specific simulation graphs are shown in Figure 9.

4.3.4. What Should Be Done in the Third Stage?

(1) University authorities should launch an emergency quarantine policy to deal with deteriorating conditions that may occur, while paying attention to other people who are not infected. It is important to determine a suitable isolation ratio. If the quarantine proportion is 100%, the cost will be too high. Considering that the epidemic condition is dynamic and unstable, the quarantine policy must be flexible in practice.

(2) Once the isolation ratio is confirmed, there is a need to allocate sufficient professional staff, including officers, doctors, volunteers, etc. To ensure that stability and orderliness in the process of epidemic control, a supporting security plan is also needed. In addition, authorities can recruit people who have no symptoms of infection and have passed the safety quarantine period to serve as temporary part-time security personnel besides the full-time security personnel.

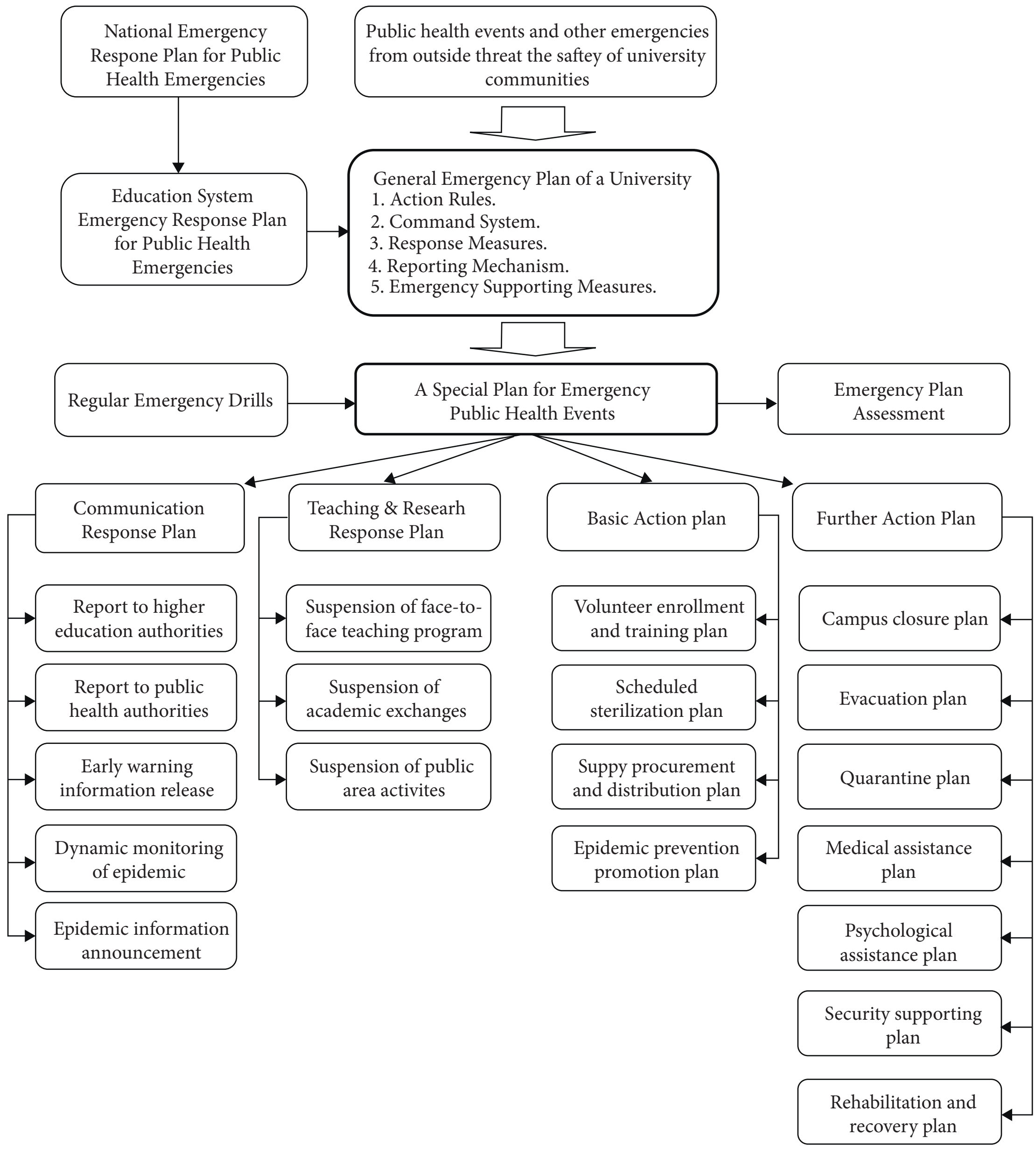


Figure 10: The framework of the emergency management system in universities.

(3) In addition to quarantine measures for infected people, self-isolation policies for other healthy people should be implemented as well until the risk is dismissed. In this period, it is necessary to supply extensive and targeted psychological assistance.

5. Conclusions and Countermeasures

5.1. Conclusions. The results of the sensitivity analysis at each stage show that there are many parameters that greatly affect the overall behavior. This study focuses on whether epidemic spread can be effectively controlled under different epidemic prevention policies. The first stage of the simulation is an extended version of the combined SIR model without reasonable feedback. In the second stage, the recovered population is added to reduce the chance of the uninfected people in the susceptible group coming into contact with other infectious groups. In the third stage, quarantine measures are added at different stages of the infection's evolution to reduce the infection rate among susceptible groups.

When an epidemic is spreading in a university, it is important to have a rapid initial response. The faster the response rate, the lower the rate of infection spread. From the case study, we found the following: First, it takes 2.25 weeks from the initial infection of one person to infect all 6743 people if there is no intervention. Second, if emergency response and medical care are considered, the peak arrival time can be shortened to 2 weeks and the peak number of infections can be reduced to 4596 people. In addition, if a quarantine policy is considered, when the isolation ratio is 90%, the total number of patients will reach a peak of 3211 in 2.125 weeks. Without considering the cost of isolation, 90% of the isolation ratio is the optimal value. In fact, regarding the COVID-19 outbreak in China, the government quickly launched an emergency response plan and implemented very strict quarantine policies at the beginning (the isolation ratio was almost 100%), which restrained the epidemic's spread in a very short time. This proved the effectiveness of a quarantine policy and supported the conclusions of this study from a practical point of view.

5.2. Countermeasures

5.2.1. Establish an Emergency Management Framework. An infection evolving simulation of epidemic spreading shows that university communities should establish an effective emergency management framework for responding to epidemics, including COVID-19 and some other public health events. The emergency response system of a university should follow the rules of the National Emergency Response Plan for Public Health Emergencies and include at least three levels of plans. The first level is the general emergency plan of a university; the second level is the special plan for emergency public health events; and finally, the third level is the specific plans in detail. The general emergency plan contains five basic rules that need to be followed. The special plan contains at least four small specific plans, and each plan includes its own response actions (including but not limited to the 19 kinds of actions in Figure 10). There is no order of priority among the actions of the four plans, which means that some actions in each specific plan can be implemented at the same time, forming linkages in the emergency response in practice.

5.2.2. Regular Emergency Drills and Assessment. Emergency drills are one of the most effective ways to control infectious diseases. In the process of university education and management, fire drills and natural disaster escape drills are often used as training subjects, but emergency drills for infectious disease outbreaks are usually ignored. After formulating an effective emergency management system, it is necessary to carry out regular drills to improve the emergency response capabilities of authorities, teachers, and students. In addition, the emergency management system should carry out a classified stress test at least each year, as a basis for an effective assessment of the system. Authorities should revise parts of the system that are not applicable according to the assessment.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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