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Virus transmission risk of college students in railway station during Post-COVID-19 era: Combining the social force model and the virus transmission model

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**Abstract**

In the post-epidemic era, people's lives are gradually returning to normal, and travel is gradually resuming. The safe evacuation of cross-regional travelers in railway station has also attracted more and more attention, especially the evacuation behavior of college students in railway station. In this paper, considering the pedestrian dynamics mechanism in the emergency evacuation process during the COVID-19 normalized epidemic prevention and control, an Agent-based social force model was established to simulate the activities of college students in railway station. Combined with the virus infection transmission model, Monte Carlo simulation was used to calculate the total exposure time and the number of high-risk exposed people in the railway station evacuation process. In addition, sensitivity analysis was conducted on the total exposure time and the number of high-risk exposed people under 180 combinations of the number of initial infections, social distance, and the proportion of people wearing masks incorrectly. The results show that with the increase of social distances, the total exposure time and the number of high-risk exposures do not always decrease, but increase in some cases. The presence or absence of obstacles in the evacuation scene has no significant difference in the effects on total exposure time and the number of high-risk exposures. During the evacuation behavior of college students in railway station, choosing the appropriate number of lines can effectively reduce the total exposure time and the number of high-risk exposures. Finally, some policy suggestions are proposed to reduce the risk of virus transmission in the railway station evacuation process, such as choosing dynamic and reasonable social distance and the number of queues, and reducing obstacles.

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1. Introduction

Since December 2019, the rapid spread of the COVID-19 epidemic has brought major challenges to public health and social security in countries around the world [1]. In order to prevent the spread of the epidemic to the maximum extent, most countries and regions have adopted blockade and restriction policies, such as blocking entry and exit, restricting traffic travel, restricting the flow of indoor places, and opening time-sharing venues [2]. The spread of the epidemic...
was effectively controlled to a certain extent through home isolation, control of social distance, closure of high-density crowd gathering places, and reduction of unnecessary offline activities [3,4]. Many countries and regions in the world have gradually stepped into the post-epidemic era. However, epidemic control in the post-epidemic era requires non-drug intervention in epidemic transmission from the perspectives of management science, transportation science, systems science and social science [5,6]. At present, China has rapidly brought the epidemic under control and entered the post-pandemic era [7]. In the post epidemic era, a large-scale outbreak is a small probability event, but the occurrence of the epidemic in individual cities will seriously affect the travel of people in that city.

The social force model is widely used to reveal pedestrian dynamics mechanism in the emergency evacuation process during the epidemic. At present, many studies have incorporated pedestrian dynamics into epidemic transmission models, which are used to analyze the time-varying physical distance transmission process in the process of individual movement [8,9]. By analyzing the characteristics of pedestrian evacuation under COVID-19, Yang et al. [10] established an improved social force model and proposed two new concepts of evacuation factor and avoidance force under COVID-19. Sparnaaij et al. [11] and Xu et al. [12] respectively assessed the risk of transmission of COVID-19 virus in restaurants and supermarkets, which identified the impact of different factors on the risk of transmission and the effectiveness of corresponding mitigation policies. Garcia et al. [13] assessed the transmission risk of COVID-19 virus in different daily living situations, including large numbers of unmasked pedestrians, by combining specific spatial models of respiratory droplet transmission with detailed field data on pedestrian trajectory and head direction.

In the application of the social force model in epidemic prevention and control, many scholars have used Agent-based model simulation to study virus transmission. By simulating human activities in different scenarios, and using the virus transmission model to calculate the infection risk of pedestrians in these scenarios when the epidemic occurs. Wang et al. [14] and Campos et al. [15] conducted a numerical simulation of the infection transmission in a fever clinic during the influenza pandemic by combining the Agent-based social force model and the infection transmission model, and evaluated the infection risk of inhaling air virus in the fever clinic. Vuorinen et al. [16] and Tsukanov et al. [17] studied the transmission risk of the COVID-19 virus in supermarkets using Agent-based methods. Marlow et al. [18] studied the risk of airborne virus transmission during cinema evacuation by constructing an Agent-based model.

Non-pharmaceutical measures such as keeping social distance can play an important role in controlling the spread of the epidemic. Sajjadi et al. [19] considered the compartment susceptible exposure infection (SEI) dynamics and indirect transmission in the agent-based model, and found that the denser the social distance, the greater the impact on exposure risk. Mohammadi et al. [20] explored the risk of airborne transmission of infectious diseases under different social distances, estimated the relative risk of viral transmission among pedestrians under different walking conditions. Cui [21] predicted the transmission trend of respiratory infectious diseases based on the exposure risk model, which can accurately predict the transmission trend of diseases from a micro perspective, and is conducive to further study of many micro disease transmission factors (such as non-walkable areas and facility layout). Tang et al. [22] revealed the impact of the flow of people in the family environment on the daily growth rate of the virus in India during the second wave of the COVID-19 pandemic, and found that the proportion of indoor transmission in the family environment was higher.

Schools are places where people are densely aggregated and have frequent contacts. Once infected cases occur, it is more prone to lead large-scale spread of the epidemic, causing a major impact on students, schools, families, society and even the country as a whole. For instance, confirmed COVID-19 cases were found in schools in Shijiazhuang, China in 2022 [23], Jilin, China in 2022 [24] and Chongqing, China in 2022 [25], which had a serious impact on the normal learning and life of teachers and students. The social force model and virus transmission model also have related applications in college epidemic prevention and control. Lee et al. [26] designed and implemented a survey of students' social distancing in educational facilities. Imbornoni et al. [27] established a simulation model to describe the current state of the canteen and designed three dining plans to determine the optimal number of students allowed into the canteen and solve the problem of low dining efficiency in the canteen.

In summary, most of the aforementioned studies have examined the application of the social force model and the virus transmission model in the emergency evacuation process on different indoor occasions during the epidemic restaurants, supermarkets, fever clinics. Few studies focused on the railway stations, which has a large flow of people gathering from the whole country. In the evacuation behavior of in railway station, if the epidemic prevention work is not proper, it is likely to cause the large-scale spread of the epidemic, causing a significant impact. In addition, the current study lacks a systematic analysis of social distancing, the proportion of people wearing masks incorrectly, obstacles and the number of queues when studying the impact on the risk of transmission of the virus during evacuation. This study combines the agent-based social force model with the virus transmission model, uses Monte Carlo simulation to calculate the total exposure time and the number of high-risk exposed people during the evacuation process, evaluates the risk in the evacuation behavior of college students in railway station, and puts forward reasonable measures and suggestions.

The rest of the paper is organized as follows. Section 2 reviews the literature on the application of social force models to epidemic control. The framework of the social forces model and the viral transmission model is described in detail in Section 2. Section 3 is the experiment and discussion results. Finally, Section 4 summarizes the conclusion and future research direction.

2. Methodology

In this section, we elaborate on the proposed social force model and virus transmission model. Social force models reproduce pedestrian movements at pick-up sites, and virus transmission models describe the risk of virus transmission from an infected to a susceptible population. We will provide detailed formulas for both modules in this section.
2.1. Social force model

The social force model [28,29] regards the human movement as the result of the joint action of the driving force, attraction force and repulsion force. It expresses the changes of pedestrian speed and acceleration in the form of Newton’s second law, constructs several forces that drive pedestrian movement, and generates mathematical equations to describe the pedestrian movement:

$$ F_i(t) = F_i^{des}(t) + \sum_j F_{ij}^{ped}(t) + \sum_w F_{i,w}^{obs}(t) $$

(1)

Where, $F_i(t)$ is a plane vector that represents the resultant force of all external forces exerted on pedestrian $i$ at time $t$, $F_i^{des}(t)$ represents the attraction of the target position to pedestrians at time $t$. $F_{ij}^{ped}(t)$ reflects the interaction force of pedestrian $j$ adjacent to pedestrian $i$ at time $t$. $F_{i,w}^{obs}(t)$ denotes the interaction force of other obstacles $w$ (such as wall and column) on pedestrian $i$ at time $t$.

The pedestrian $i$ of mass $m_i$ travels with speed $v_i^0$ in the expected direction $e_i^0$ within the relaxation time $\tau_i$ (the shorter the time, the closer the pedestrian gets to the expected direction and speed). $v_i(t)$ and $e_i(t)$ are used to represent the velocity and expected direction at time $t$, then $F_i^{des}(t)$ can be expressed as

$$ F_i^{des}(t) = m_i \frac{v_i^0 e_i^0 - v_i(t)e_i(t)}{\tau_i} $$

(2)

Generally speaking, the interaction force $F_{ij}^{ped}(t)$ between pedestrians is a repulsive force, which is divided into two parts, the social force at the psychological level and the contact force at the physical level. As shown in Eq. (3).

$$ F_{ij}^{ped}(t) = \left\{ \begin{array}{ll} A \exp \left( \frac{r_{ij}-d_{ij}(t)}{B} \right) + Cg \left( r_i + r_j - d_{ij}(t) \right) & \quad n_{ij}(t) \\
0 & \quad \text{otherwise} \end{array} \right. $$

(3)

The pedestrian in the model is simplified as a circle, $r_i$ and $r_j$ are both radii, and $d_{ij}(t)$ is the distance between the center points of pedestrian $i$ and $j$ at time $t$. $n_{ij}(t)$ represents the unit vector at that moment, whose direction is always from pedestrian $j$ to $i$. Parameters $A$, $B$ and $C$ are mainly used to calibrate the strength of the force between pedestrians as well as the range and distance maintained. Their values are mainly influenced by the specific activity scenario. $g(x)$ is a function of counteracting the repulsive force of body compression at pedestrian contact and is equal to zero only at pedestrian contact.

$$ g(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases} $$

(4)

The interaction force $F_{i,w}^{obs}(t)$ between pedestrian $i$ and other obstacles (such as wall, column, etc.) can be written

$$ F_{i,w}^{obs}(t) = \left\{ \begin{array}{ll} A \exp \left( \frac{r_i-d_{i,w}(t)}{B} \right) + Cg \left( r_i - d_{i,w}(t) \right) & \quad n_{i,w}(t) \\
0 & \quad \text{otherwise} \end{array} \right. $$

(5)

Where, $d_{i,w}(t)$ is the distance between pedestrian $i$ and other obstacles $w$ at time $t$. $n_{i,w}(t)$ is the unit vector at this moment, and its direction is always from obstacle $w$ to pedestrian $i$.

2.2. Infection transmission model

In the process of evacuation, no matter it is close to the infected individuals or located in the coughing area, it has the potential risk of spreading infectious diseases. Therefore, in the infection transmission model, the general exposure time $T_i$ of student $i$ is obtained by the accumulation of contact exposure time $T_i^{ct}$ and cough exposure $T_i^{cg}$. The calculation formula of general exposure time $T_i$ is as follows:

$$ T_i = T_i^{ct} + T_i^{cg} $$

(6)

Contact exposure time refers to the sum of physical contact times between students $i$ and each infected individual in their vicinity. As shown in formula (7).

$$ T_i^{ct} = \sum_{t=1}^{t_i^{enter}} \sum_{m=1}^{M(t)} \lambda_{i,m}(t) $$

(7)

Where, $t_i^{enter}$ indicates the time when the student $i$ starts to enter the evacuation process (that is, the time when the student appears from the exit); $t_i^{exit}$ represents the time when student $i$ finishes all processes; $m$ stands for infected individuals; $M(t)$ represents the number of infected individuals in the place at time $t$.

When considering the aerosol transmission of large droplets exhaled when speaking, 1.6–3.0 m is a safe social distance [30]. The radius of the safe distance $D$ adopted in this study is 1.6 m. $\lambda_{i,m}(t)$ represents whether student $i$ is
exposed to the influence range of infected individual $m$ at time $t$, and the judgment criteria are shown in Formula (8):

\[
\lambda_{i,m}(t) = \begin{cases} 
1, & \text{if } d_{i,m}(t) \leq 1.6 - r_m \\
0, & \text{otherwise}
\end{cases}
\]  

(8)

Where, $d_{i,m}(t)$ represents the distance between student $i$ and the infected individual $m$ at time $t$; $r_m$ is the body radius of infected person $m$.

According to the requirements of epidemic prevention and control, all students must wear masks correctly during the evacuation of the railway station. Masks should cover their mouth, nose and chin, and nose clips should be compressed. Masks should be replaced in time if they become dirty, deformed, damaged or smelly. Wear each mask for no more than 4 h in total. Do not wear the mask upside down or inside out, and do not expose your nose while wearing the mask. But in practice, there are still some students who do not fit their faces well when wearing masks. If there is a gap between the mask and the face, air flows into the gap when a person breathes. Tests have found that the rate of external bacterial leakage under such conditions reaches 100%.

In this section, cough exposure time is calculated by adding up the number of physical contacts of student $i$ who is not wearing a mask properly and each coughing infected individual in their immediate vicinity. Compared with contact exposure, cough exposure spread farther, but lasted for a shorter time. It is assumed that the infected individual coughs every 15 s and the area affected by the virus is circular (9). The formula for calculating cough exposure time $T_{cg}^i$ is as follows:

\[
T_{cg}^i = \sum_{t=\text{exit}_i}^{t=\text{enter}_i} \sum_{n=1}^{N(t)} \mu_{i,n}(t) 
\]

(9)

Where, $n$ is an infected individual who is coughing; $N(t)$ is the number of infected individuals who are coughing at time $T$; $\mu_{i,n}(t)$ indicates whether student $i$ is exposed to the affected area of the coughing infected individual $n$ at time $t$. The judgment criteria are shown in Formula (10):

\[
\mu_{i,n}(t) = \begin{cases} 
1, & \text{if } d_{i,n}(t) \leq R_n \\
0, & \text{otherwise}
\end{cases}
\]  

(10)

Where, $d_{i,n}(t)$ represents the distance between student $i$ and the infected individual $n$ who is coughing at time $t$.

The average cough distance of the volunteers, the radius of the cough area $R_n$ is set to 2.5 m, and the infection time of the cough lasts for an average of 5 s outdoors [31].

In order to quantify the risk of COVID-19 transmission during the evacuation behavior of college students in railway station, the total exposure time $T_{inf}$ and the number of high-risk exposed people $C_{\text{risk}}$ are calculated according to the general exposure time $T_a$ of each student.

Total exposure time $T_{inf}$ refers to the sum of the exposure time of all students staying throughout the evacuation process. As shown in Formula (11):

\[
T_{inf} = \sum_i T_i
\]

(11)

Considering the extremely high external bacterial leakage rate when masks are not properly worn as required, this section also uses the number of high-risk exposed people who wear masks incorrectly as an important indicator to evaluate the risk of virus transmission during the evacuation behavior of college students in railway station.

The number of high-risk exposed people $C_{\text{risk}}$ refers to the number of people wearing masks incorrectly and were exposed for more than 15 s during the whole process. $T_a$ represents the general exposure time of students who wear masks incorrectly. The number of high-risk exposed people $C_{\text{risk}}$ is calculated as shown in Formula (12):

\[
C_{\text{risk}} = \sum_i \psi(T_a)
\]

(12)

Where, $\psi(T_a)$ represents whether student $a$ is a high-risk exposed population, and the judgment criteria are shown in Formula (13)

\[
\psi(T_a) = \begin{cases} 
1, & \text{if } T_a > \overline{T} \\
0, & \text{otherwise}
\end{cases}
\]  

(13)

Suppose $\overline{T}$ represents an exposure time of 15 s.

3. Experiment

In this section, we first describe the dataset and data preprocessing. Then we describe the experimental settings. Finally, model results are analyzed to explore the changes of the total exposure time and the number of high-risk exposed people under 180 combinations of the three parameters of the number of initial infections, social distances, and the proportion of people wearing masks incorrectly.
Table 1

| Serial number | Time of arriving | Number of persons | Serial number | Time of arriving | Number of persons |
|---------------|------------------|-------------------|---------------|------------------|-------------------|
| 1             | 10:00            | 7                 | 2             | 10:02            | 1                 |
| 2             | 10:02            | 1                 | 3             | 10:10            | 1                 |
| 3             | 10:10            | 1                 | 4             | 10:15            | 7                 |
| 4             | 10:22            | 1                 | 5             | 10:26            | 1                 |
| 5             | 10:30            | 6                 |               |                  |                   |

Fig. 1. College students evacuation process and time consumption.

3.1. Dataset description

Data is provided by the Student Service Center of Hebei University of Technology. In order to ensure that students returning to Tianjin, China from other places can return to school safely and smoothly, a total of 352 members of the student service center and staff volunteers devoted themselves to the pick-up work at Tianjin railway station, Tianjin South Railway Station, Tianjin West railway station and Binhai airport, realizing point-to-point, door-to-door transfer into direct delivery Students returned to school from April 26 to 27, 2022. The pick-up service covers all students who return to Tianjin, China from other places, with the careful arrangement and scientific scheduling to meet the needs of students returning to school by public transportation to the greatest extent. The school arranges the picking-up time from 7:00 to 22:00. Students who arrive at the station during other periods will be picked up by their own vehicles. In this study, 625 students returning to Tianjin South Railway Station of a university in Tianjin, China on April 26, 2022 were taken as the research objects to obtain the actual arrival data of students returning to Tianjin, China. Table 1 shows the arrival time and number of students in the 10:00–11:00 time period.

In the evacuation of the railway station work, coordinate Tianjin South Railway Station in advance to determine the pick-up location and the bus location. Design clear and definite pick-up signs and determine the positions of the guides to ensure that students can find the guides at the fastest speed and arrive at the pick-up site with the shortest path, avoiding excessive contact with other personnel. Returning students get off the train at Tianjin South Railway Station and exit through the exit on the first floor. After the students arrive at the pick-up location, the staff will guide the students to perform hand disinfection, measure the body temperature, check the health code, the travel code and the school entry approval code, and verify whether the students meet the requirements for returning to school. Then the staff disinfected the students’ luggage, and the students replaced the N95 masks provided by the school. Finally, according to the campus where the students are located, let the students who meet the conditions for returning to school scan the “site code” of the dormitory campus, and arrange for the students to board the bus according to the student dormitory campus. Fig. 1 shows the whole process of the evacuation behavior in railway station.

Students need to go through eight steps from getting out of the station to getting on the bus. Due to the space limitation, students at the station formed two lines to carry out each step in an orderly manner. It takes about 4–6 s for hand disinfection, temperature measurement, health code check, travel code check, school entry approval code check, luggage disinfection and mask change. Due to the network influence, it takes about 9–10 s to scan the site code.

3.2. Experimental setting

Based on the social force model, this section establishes the evacuation behavior of college students in railway station model in Anylogic’s Pedestrian Library. The established pedestrian model effectively describes the activities of returning
students in the evacuation of the railway station, and obtains the activity information of students during the whole process.

Firstly, it was simulated into the main interface of the Anylogic software concerning the plane schematic diagram of the square in front of the Tianjin South Railway Station, and then a basic simulation environment along its boundary at a scale of $1 \text{ m} = 6.8 \text{ px}$ was simulated according to the schematic diagram. Relevant elements were set in the environment model, including walls, entrances and exits, pick-up registration area, services (hand disinfection, temperature measurement, etc.). The pedestrian comfortable speed is uniform $(0.5,1)$ meters per second, initial speed is $(0.3,0.7)$ meters per second and diameter: uniform $(0.4,0.5)$ meters. The final operation of the model and the partial diagram of the model operation are shown in Fig. 2.

Students first arrive at the exit (i.e., position 1 in Fig. 2), then walk to the pick-up registration area (i.e., position 2 in Fig. 2), and follow the direction indicated by the red arrow to perform hand disinfection, temperature measurement, code checking and other processes. After completing all procedures, they walk to position 3 and get on the bus. If any abnormality is found in the process of evacuation, such as the discoloration of the student’s health code, the student will be taken to the isolation place immediately to avoid affecting the progress of other students. Therefore, this study assumes that all links are carried out normally and smoothly without abnormal phenomena.
3.3. Experimental results and discussion

Maintaining a certain social distance and wearing masks correctly are both effective ways to prevent the COVID-19 transmission from person to person. In order to examine the effects of different social distances and different proportions of people wearing masks incorrectly on the total exposure time and the number of high-risk exposed people, six social distances and five proportion of people wearing masks incorrectly ($P$) were introduced, which are 0.6, 0.8, 1.0, 1.2, 1.4, 1.6 and 10%, 20%, 30%, 40%, 50%, respectively. At the same time, in order to investigate the impact of different numbers of initial infections on students, five kinds of initial infection numbers were introduced, namely 5, 10, 15, 20, 25 and 30.

In the Monte Carlo simulation, the initial infected individuals were randomly assigned from students of all susceptible populations, and then the total exposure time and the number of high-risk exposed people throughout the whole evacuation process were calculated. It is found that the results of Monte Carlo simulation running 200 times were very close to those of 500 times. In order to improve the running efficiency, the Monte Carlo simulation was set to run 200 times. Then the total exposure time and the number of high-risk exposed people under different parameter values were calculated from 200 tests.

The Agent-based model simulates each student’s entry time, departure time, position at each moment, contact time and the distance between each student. Monte Carlo simulation program was used to randomly determine who was infected according to the number of initial infections. Then, according to the time information and corresponding location of the infected person, the program judged whether the susceptible person and the infected person were in the corresponding influence range at the same time, and calculated the total exposure time and the number of high-risk exposed people under the corresponding parameters through 200 iterations.

3.3.1. Sensitivity analysis of the proportion of people wearing masks incorrectly to the total exposure time and the number of high-risk exposed people

Monte Carlo simulation was used to obtain the estimated value of the total exposure time under 180 combinations of the number of initial infections, social distance and the proportion of people wearing masks incorrectly. Fig. 3 shows the trend chart of the total exposure time under different combinations of parameters.

As shown in Fig. 3(a)–(f), when the number of initial infections and social distance are fixed, the proportion of people wearing masks incorrectly increases exponentially, and the growth of the total exposure time is also close to a multiple relationship. Therefore, non-standard mask wearing behavior can easily cause serious transmission risks. By comparing Fig. 3(a)–(f), it is obvious that with the doubling of the number of initial infections from 5, 10, 15, 20, 25, and 30, the total exposure time is close to doubling. Therefore, it is of great significance for students to return to school safely to minimize the risk of infection before returning to school. In Fig. 3(a), the number of initial infections was 5, and the proportion of people wearing masks incorrectly was 10%, as the social distance increased from 0.6 m to 0.8 m, the total exposure time decreased significantly, showing a great sensitivity. However, when the social distance was increased to 1.0 m, 1.2 m, 1.4 m and 1.6 m, the change of the total exposure time was not obvious and the sensitivity was small. When the proportion of people wearing masks incorrectly was 40% and 50%, the total exposure time decreased more significantly when the social distance was expanded from 0.6 m to 0.8 m. However, when the social distance was increased from 1.2 m to 1.4 m, the total exposure time with the proportion of people wearing masks incorrectly was 40% increased instead. This is due to each step in the pick-up registration area requiring a corresponding time. Therefore, during the peak hours when students arrive, there will be small-scale gatherings at the entrance of the queue, and greater social distance will result in more crowd gatherings, as shown in Fig. 2. Similar phenomena also occur under other parameters. For instance, when the number of initial infections is 10, the proportion of people wearing masks incorrectly is 30%, and the social distance increased from 1.4 m to 1.6 m, the total exposure time has an obvious upward trend. Notably, total exposure time may instead increase with greater social distancing. It is necessary to reasonably arrange the social distance according to the actual situation and site layout.

In order to further quantify the transmission risk of COVID-19 during the evacuation behavior of college students in railway station, it is necessary to investigate the impact of different social distances and different proportions of people wearing masks incorrectly on the number of high-risk exposed people. Similar to the results on the total exposure time, this section examines the sensitivity of the number of high-risk exposed people during the whole evacuation process to different the number of initial infections, different social distances and different the proportion of people wearing masks incorrectly, and propose corresponding prevention and control measures according to the sensitivity.

Monte Carlo simulation was used for many times to obtain the estimated value of the number of high-risk exposed people under 180 combinations of three parameters. Matlab software was used to draw the trend chart of the number of high-risk exposed people under different combinations of parameters, as shown in Fig. 4.

As can be seen from Fig. 4(a)–(f), when the number of initial infections and social distance are constant, the number of high-risk exposed people also increases close to a multiple relationship as the proportion of people wearing masks incorrectly increases exponentially. Therefore, wearing masks correctly plays a crucial role in the prevention and control of the epidemic. In the evacuation behavior of college students in railway station, if we can standardize the wearing of masks, cooperate with the implementation of disinfection, maintain a reasonable social distance and other measures, the epidemic will be contained in the bud, and ensure the smooth evacuation of the railway station. By comparing Fig. 4(a)–(f),
it can be seen that as the number of initial infections increases, the number of high-risk exposed people also increases significantly. Therefore, it is necessary to grasp the situation of students in time, so as not to lead to a larger number of initial infections, thereby increasing the infectivity. In Fig. 4(a), the number of initial infections is 5, when the probability of the proportion of people wearing masks incorrectly is 10%, as the social distance gradually increases from 0.6 m to 1.6 m, the relative change of the number of high-risk exposed people is relatively small and the sensitivity is low. However, when the proportion of people wearing masks incorrectly was 50%, as the social distance increased from 0.6 m to 0.8 m and 1.0 m, the relative changes of the number of high-risk exposed people were more significant and the sensitivity was high. These changes demonstrate that wearing masks correctly plays a key role in prevention and control during the whole evacuation process. The higher the proportion of people wearing masks correctly, the less sensitive the number of high-risk exposed people will be with the change of social distance. In this way, the social distance can be appropriately reduced to avoid the crowd gathering at the entrance of the queue caused by excessive social distance. When the proportion of people wearing masks incorrectly was 50%, the number of high-risk exposed people tended to rise when social distancing increased from 1.0 m to 1.2 m. At the same time, the proportion of people wearing masks incorrectly was 40%, and the number of high-risk exposed people also increased when social distancing increased from 1.2 m to 1.4 m. The reason...
for this change maybe that when social distance increases, small-scale gather at the entrance of the queue, leading more contact with infected individuals, as shown in Fig. 2. The same rule also exists in Fig. 4(b)–(f).

3.3.2. Sensitivity analysis of obstacles to the total exposure time and the number of high-risk exposed people

As shown in Fig. 2, during the peak hours of students’ arrival, there will be small-scale gatherings at the entrance of the queue, which will increase the total exposure time and cause a more serious risk of virus transmission, which is not conducive to the safe evacuation of college students in railway station. Then, we mainly focus on the small-scale gathering at the entrance of the queue by separated scenarios the presence or absence of obstacles respectively.

Fig. 5 shows the change trend of the total exposure time after removal of obstruction. The number of initial infections was set as 5, the proportion of people wearing masks incorrectly was 50%, and the social distance was set as 0.6 m, 0.8 m, 1.0 m, 1.2 m, 1.4 m, 1.6 m. Curve Y represents the change of the total exposure time with social distance when an obstacle (law enforcement kiosk) is present, and curve N represents the change of the total exposure time with social distance when an obstacle (law enforcement kiosk) is removed. When social distance increased from 0.6 m to 0.8 m, the total exposure time of curves Y and N decreased significantly, but the gap between curves Y and N was not very large. When the social distance increased from 0.8 m to 1 m, the total exposure time of curve Y decreased significantly. However, the total exposure time of curve N was higher than that of curve Y, although it has a downward trend. In addition, when the
social distance increased from 1 m to 1.2 m, the total exposure time of curve Y was basically unchanged due to obstacles (law enforcement kiosks). In curve N, the total exposure time showed an obvious downward trend due to the elimination of obstacles (law enforcement kiosks). When the social distance increases from 1.4 m to 1.6 m, the total exposure time of curve N tends to increase due to the limitation of the site. Therefore, when choosing a pick-up site, the layout of the site should be reasonably considered, other buildings should be avoided, and a without obstacles site should be selected as much as possible.

Similar to the results on the total exposure time, the effect on the number of high-risk exposed people after avoiding obstacles (law enforcement kiosks) is considered. Fig. 6 shows the trend of the number of high-risk exposed people after the removal of barriers (law enforcement kiosks). The number of initial infections was set as 5, the proportion of people wearing masks incorrectly was 50%, and the social distance was set as 0.6 m, 0.8 m, 1.0 m, 1.2 m, 1.4 m, 1.6 m. Curve Y represents the change of the number of high-risk exposed people with social distance when the obstacle (law enforcement kiosk) is present, and curve N represents the change of the number of high-risk exposed people with social distance when the obstacle (law enforcement kiosk) is removed. When social distance increased from 0.6 m to 0.8 m, the number of high-risk exposed people on curves Y and N decreased significantly, but the gap between curves Y and N were not very large. When social distance increased from 0.8 m to 1.0 m, the number of high-risk exposed people on curve Y decreased significantly. However, the number of high-risk exposed people of curve N was higher than that of curve Y, although it has a downward trend. In addition, when the social distance increased from 1.0 m to 1.2 m, the number of high-risk exposed people based of curve Y increased slightly due to obstacles (law enforcement kiosks). Curve N shows an obvious downward trend due to the elimination of obstacles (law enforcement kiosks). When the social distance is increased from 1.4 m to 1.6 m, the number of high-risk exposed people on curve N tends to increase due to the limitation of the site. As can be seen from Fig. 6, the number of high-risk exposed people with and without obstructions (law enforcement kiosks) decreased, but the effect was not significant.
3.3.3. Sensitivity analysis of queue number to the total exposure time and the number of high-risk exposed people

In order to alleviate the crowd gathering at the entrance of the queue during the peak hours of students’ arrival and avoid a more serious risk of virus transmission, this section mainly investigate the impact of the number of queues in the evacuation process on the total exposure time and the number of high-risk exposed people.

In the actual evacuation of the railway station, arriving students form two lines to carry out each link orderly. In order to compare the impact of the number of queues on the total exposure time, a comparative analysis was conducted by setting the number of queue lines as 1, 2 and 3, respectively. Fig. 7 shows the trend of the total exposure time under the different number of queues. Setting the number of initial infections was 5, the proportion of people wearing masks incorrectly was 50%, and the social distance was set as 0.6 m, 0.8 m, 1.0 m, 1.2 m, 1.4 m, 1.6 m. When the number of queues is 1, the total exposure time increases sharply due to a larger crowd gathering at the entrance of the queue, and the evacuation speed is slow, resulting in a high risk of virus transmission and low efficiency. When the number of lines was 3, the crowd gathering at the entrance of the line was alleviated to a certain extent, and the total exposure time decreased compared with that when the number of lines was 2, reducing the risk of exposure to the virus. When the flow of people is constant, increasing the number of queues can reduce the total exposure time, but with the gradual increase in the number of queues, the decreasing effect will be significantly reduced.

Fig. 8 shows the trend of the number of high-risk exposed people under the different number of queues. Setting the number of initial infections was 5, the proportion of people wearing masks incorrectly was 50%, and the social distance was set as 0.6 m, 0.8 m, 1.0 m, 1.2 m, 1.4 m, 1.6 m. When the number of queues is 1, due to the slow evacuation speed, there will be a larger crowd gathering at the entrance of the queue, and the number of high-risk exposed people will increase sharply, resulting in a high risk of virus transmission. When the number of lines was 3, the crowd gathering at the entrance of the line was alleviated to some extent, and the number of high-risk exposed people decreased compared with that when the number of lines was 2, reducing the number of students with high-risk exposure. When the flow of people is constant, increasing the number of queues will reduce the number of high-risk exposed people, but with the
gradual increase of queues, the decreasing effect will be significantly reduced. Therefore, a reasonable number of queues should be set up to reduce the number of high-risk exposed people, improve evacuation efficiency and maximize resource utilization.

4. Conclusions and recommendations

The outbreak of COVID-19 poses a great threat to the whole world. Although the epidemic situation in China is basically under control, small-scale outbreaks still occur frequently, which is also a great challenge for the safe evacuation behavior of college students in railway station. This study explores the changes of the total exposure time and the number of high-risk exposed people when the number of initial infections is 5, 10, 15, 20, 25 and 30, the social distance is 0.6 m, 0.8 m, 1.0 m, 1.2 m, 1.4 m and 1.6 m, and the proportion of people wearing masks incorrectly is 5%, 10%, 15%, 20%, 25% and 30%. In addition, this paper analyzes the two situations of removing obstacles (law enforcement kiosks) and queueing the number of queues. Finally, the relevant measures and suggestions are put forward for the evacuation behavior of college students in railway station. Those results show that:

(1) As the number of initial infections increased exponentially from 5, 10, 15, 20, 25 and 30, the total exposure time and the number of high-risk exposed people also showed a trend of multiple growth. Therefore, before students return to school, they should strictly verify their travel trajectory and temperature monitoring for the 14 days before returning to school, so that students with a travel history in medium-high risk areas can postpone their return to school, and make arrangement after the risk is reduced, so as to reduce the risk of virus transmission from the source. For students who have already infected and arrived at the station, measures should be taken to isolate them in time to avoid their contact with other students, which may reduce infection risks. Arranging for students at risk of transmission to postpone their return to school is very effective in reducing the risk of transmission of the virus during students returning to school.

(2) If it is found that some students wear masks incorrectly, the volunteer can remind them in time to reduce the exposure time of students to the virus and reduce the risk of transmission. The proportion of people wearing masks incorrectly decreased exponentially, and the total exposure time and the number of high-risk exposed people number also nearly doubled. Increasing the proportion of people wearing masks correctly in accordance with epidemic prevention requirements is very significant to reduce the risk of virus transmission when students return to school.

(3) The length of social distance should be reasonably arranged according to the actual situation (such as the number of people arriving at the station) and the layout of the site. In Figs. 3(a) and 4(a), when the social distance was 1.0 m and 1.2 m, the total exposure time tended to be relatively flat, but the number of high-risk exposed people increased slightly when the proportion of people wearing masks incorrectly was 50%. Therefore, when the proportion of wearing masks correctly was increased, the social distance could be set to 1.0 m. In order to reduce the crowd gathering at the entrance of the queue, it is reasonable to ensure that students wear masks correctly and shorten the social distance to 0.8 m during peak hours.

(4) When selecting a pick-up site, it is better to choose a without obstacles site to avoid other building obstructions during peak traffic hours, which will increase the total exposure time and the number of people exposed to high risks. In Figs. 5 and 6, although the total exposure time and the number of high-risk exposures people have little difference between the presence of obstacles and the absence of obstacles, the impact of obstacles on the evacuation process should be avoided as far as possible in consideration of the risk during evacuation.

(5) In order to reduce the crowd gathering during peak hours of crowd flow, a reasonable number of queues should be selected according to the actual total number of people arriving at the station. In Figs. 7 and 8, when the number of queues increased from 1 to 3, both the total exposure time and the number of high-risk exposed people decreased significantly. However, as the number of queues gradually increased, the relative changes of the total exposure time and the number of high-risk exposed people decreased significantly. Therefore, increasing the number of queues is meaningful to reduce the total exposure time and the number of high-risk exposed people when there are more people. However, blindly increasing the number of queues will not significantly reduce the risk of infection, and will also waste human resources. It is necessary to choose a reasonable number of queues according to the actual situation to ensure safe and efficient evacuation process.

This study has several limitations. Firstly, we only compared the relative risk, ignoring the influence of the virus shape and transmission path during the spread of the virus. In addition, we did not consider the transmission risk with the change of virus dose and concentration during virus transmission. Further studies can be conducted in the following directions. We can further analyze the whole evacuation process. It remains to be studied whether there will be different behavior characteristics during the evacuation process due to the difference in the proportion of pedestrians who wearing masks incorrectly, the number of initial infections and social distance. In this paper, the total exposure time and the number of high-risk exposed people between students and infected individuals were considered, but the virus form, the number, the transmission distance, the transmission path and the transmission angle during the transmission of the virus would affect the risk of transmission. Therefore, the theory based on the combination of social forces and infection transmission model needs to be further studied. At the same time, making full use of pedestrian infrastructure, further optimizing site layout design, dynamically controlling pedestrian flow, and customizing control strategies during the normalized epidemic prevention and control will be a focus of future research.
CRediT authorship contribution statement

Hongjun Cui: Conception, Funding acquisition. Jiping Xie: Conception, Methodology, Writing – original draft, Writing – review & editing. Minqing Zhu: Methodology, Funding acquisition. Xiaoyong Tian: Investigation. Ce Wan: Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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