Risk assessment of COVID-19 infection for subway commuters integrating dynamic changes in passenger numbers

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Abstract
The COVID-19 global pandemic has had a significant impact on mass travel. We examined the risk of transmission of COVID-19 infection between subway commuters using the Susceptible Exposed Infected Recovered (SEIR) model. The model considered factors that may influence virus transmission, namely subway disinfection, ventilation capacity, average commuter spacing, single subway journey time, COVID-19 transmission capacity, and dynamic changes in passenger numbers. Based on these parameters, above a certain threshold (25 min), the risk of infection for susceptible people increased significantly as journey time increased. Average distance between commuters and levels of ventilation and disinfection were also important influencing factors. Meanwhile, the model also indicated that the risk of infection varied at different times of the day. Therefore, this paper recommends strengthening ventilation and disinfection in the carriages and limiting the time of single journeys, with an average distance of at least 1 m between passengers. In this light, subway commuters need to take proactive precautions to reduce their risk of COVID-19 infection. Also, the results show the importance of managing subway stations efficiently during epidemic and post-epidemic eras.

Keywords COVID-19 · SEIR model · Subway carriage · Infection risk · Ventilation · Journey time

Introduction
The rapid spread of COVID-19 has caused damage to human health and dramatically impacted the global economy, including effects on logistics and passenger transportation (Ikram et al. 2021). Considerable evidence has established that close contact with COVID-19-infected individuals increases the risk of infection (Lee and Jung 2019; Rea et al. 2007; Zhang et al. 2018; Chen et al. 2021). It has been demonstrated that aerosol transmission is an essential route of COVID-19 transmission and that this type of airborne virus can be transmitted by non-human contact within a vehicle (Liu et al. 2017; Marin-García et al. 2021; Miller et al. 2021). The ability of viruses to spread is also influenced by the medium, for instance, air renewal, temperature, and solar radiation (Hernández-Orallo and Armero-Martínez 2021; Ikram et al. 2020; Coccia, 2020; 2021a).

The airtightness of indoor environments creates favorable conditions for the transmission of viruses. It is worth noting that, in contemporary society, people spend more than 80% of their time indoors (including in the carriages of vehicles), which is detrimental to the prevention and control of epidemics (Klepeis et al. 2001). During the COVID-19 outbreak, commuters tried to use public transportation (including buses and subways) as little as possible to avoid becoming infected. In general, the use of public transportation decreases dramatically during a pandemic. However, once the epidemic is effectively under control, the use of public transportation becomes renormalized. The relatively small distance between commuters in subway carriages and stations leads to a higher risk of epidemic transmission (Setti et al. 2020; Sorokowska et al. 2017). For example, viral droplets can spread rapidly (10 m/s) if an asymptomatic patient coughs in a subway carriage without a mask (Buonanno et al. 2020a).
The spread of COVID-19 is influenced by local demographic and socioeconomic factors, showing variability in spatial distribution (Im and Kim 2021). Although prevention and control mechanisms for COVID-19 vary between countries, the practical measures taken (vaccine, home quarantine, financial investment, etc.) have resulted in a significant decrease in the average COVID-19 mortality rate, compared with the beginning of the pandemic (Coccia, 2021b, c, d; 2022). Many useful results have emerged from studies of epidemiological transmission in relation to transport. For example, researchers have predicted numbers of infections (Yang et al. 2009), evaluated the effectiveness of transport management preventive measures, and determined critical parameters for transmission models (Masuda 2010; Zhang et al. 2015; Sun et al. 2021). However, many studies on epidemiological transmission mechanisms in transportation lack a micro-level analysis. Therefore, the risk of COVID-19 infection among commuters in relatively enclosed compartments (buses, subways, and trains) and the effectiveness of infection prevention measures taken by transport authorities and passengers need to be studied in greater depth.

In the early days of the COVID-19 outbreak and the post-epidemic era, public transportation was frequently used, especially in larger cities where commuters have to use the subway to travel to work. Therefore, the primary objective of this research was to quantify the risk to commuters of contracting an infection during their subway commute. Analysis of patients with COVID-19 has shown that the SARS-COV-2 virus is highly transmissible, with an average incubation period of up to 14 days (Wu et al. 2020). In theory, susceptible and infected individuals need to be in a relatively confined space and relatively close together for a virus to spread by air droplets. In addition, as contact time increases, the chance of infection will increase. Therefore, it is essential to quantify the risk of passengers becoming infected by COVID-19 in subway carriages.

To date, there has been little research focusing on the risk of infection among commuters using public transportation. Furthermore, the assessment of infection risk throughout journeys may be overly idealized. The boarding and alighting of passengers at stations can cause a reorganization of passengers in the subway carriage, which affects the physical surroundings of the passengers and changes the risk of infection. Based on the above background, this study aims to contribute to the fight against COVID-19 through the following aspects:

1. 
2. 
3. 

Overall, this study identifies the mechanism of changes to transmission risk and provides theoretical support for epidemic prevention and control measures. Furthermore, we recommend ways to optimize prevention and control strategies. The findings therefore serve as a guide to enable informed decisions about outbreak prevention and control in the post-COVID-19 era and potential subsequent major public health crises.

Materials and methods

Sample and data

This study was conducted on the urban rail transit system in Xi’an. The selected study station was DYT, which is located at the interchange of lines 3 and 4. To determine the parameter changes for different scenarios caused by commuters boarding and alighting from trains, the Automatic Fare Collection (AFC) system was used to collect data from all 87 station entrances and exits. Figure 1 illustrates the location of the city of Xi’an in China and the distribution of its subway lines. It is worth noting that only four lines were operating in Xi’an at the time of this data analysis and survey.

Subway swipe data collected by the AFC system between January 1, 2020, and July 30, 2020, showed that there was a substantial impact on subway passenger numbers, with the majority of subway stations witnessing a steep decline. Figure 5 (Appendix) depicts the city’s daily passenger flow for 2020. The data on subway passenger flow began to improve progressively at the end of March; thus, the sample week for the post-epidemic period was chosen as July 20–26. Although the 1-week sample size may not reflect changes in passenger volume throughout the whole period, this study focuses on how passenger travel characteristics vary over times of day. Table 1 shows the average inbound passenger numbers for the two selected stations at different times of day.

Model variables

For the base model, we used a real-life subway scenario in order to determine specific factors influencing the risk of infection. The total length of commuter journeys on the subway did not generally exceed one hour. Within an hour, new infections of the virus do not continue to spread to more susceptible people in time t in a real-world situation. Table 2 lists the factors affecting the risk of infection.

Models and data analysis procedure

The transmission of virus between commuters is affected by many complex factors. The objectives of this study were to reveal the extent to which preventive measures reduce the risk of infection in commuters and quantify the magnitude of the risk of infection in subway carriages. This
research focused on passengers who were not wearing masks. It has been shown that although wearing a mask in public reduces the risk of infection, it does not entirely guarantee protection from COVID-19 infection, which may be strongly related to the mode of the virus (Chen et al. 2021; Clase et al. 2020). In addition, the effectiveness of the masks worn by commuters for blocking the virus varies greatly. Thus, in order to quantify the risk of infection for passengers at different times of day, the effect of masks on virus transmission was not included in this study. Furthermore, only airborne transmission of the virus in the form of aerosols was considered during passenger journeys (the risk of transmission via other channels was not evaluated as it was regarded as very low). Therefore, the following reasonable assumptions were made:

(1) We assumed that each individual had the same ability to resist infection; the value used was the average of all susceptible populations.

(2) We assumed that commuters were not gathered together in the carriage (that is, the relative distance between commuters is equal).

Table 2 Description of factors influencing the risk of infection

| Parameter | Units | Definition | Explanation |
|-----------|-------|------------|-------------|
| $t$ | min | Duration of journey | The models show that the less time spent in contact, the lower the infection rate |
| $d$ | m | Distance between people in the carriage | The model shows that the larger the value of $d$, the lower the infection rate |
| $w$ | - | Ventilation capacity | Depends on site capabilities |
| $g$ | - | Facility disinfection level | |
| $R_0$ | - | COVID-19 transmission capability | (Wu et al. 2020) gives $R_0 = 2.68$ |
(3) Air circulation caused by the ventilation of the train due to its motion during subway journeys was not considered.

During subway journeys, the transmission of infectious diseases by air requires the following two conditions: that people stay in the carriage for a relatively long time, and that infected and vulnerable people come into close contact. Under these circumstances, an infected person can spread the virus to other passengers in the carriage. Therefore, the mechanism of the infection process can be described using the classic Susceptible Exposed Infected Recovered (SEIR) model (He et al. 2020). The SEIR model divides specific groups into four categories: (i) type S refers to susceptible people (those who are not yet infected but lack immunity, and who may therefore contract the disease when they come into contact with infected people); (ii) type E represents exposed people (those infected with the virus who are still in the incubation period—this group will not retransmit the virus to others but will switch to type I as the incubation period ends); (iii) type I refers to infected people, that is, individuals with the SARS-COV-2 virus in their bodies (the incubation period of SARS-COV-2 is relatively long, and frequently an infected person does not realize that they are carrying the virus); and (iv) type R refers to people who have recovered from the virus (the virus is eliminated within a certain period of time and antibodies are produced). These four categories of people comply with the following formulas:

\[
N(t) = S(t) + E(t) + I(t) + R(t) \quad (1)
\]

\[
s(t) = \frac{S(t)}{N(t)}, e(t) = \frac{E(t)}{N(t)}, i(t) = \frac{I(t)}{N(t)}, r(t) = \frac{R(t)}{N(t)} \quad (2)
\]

In these formulas, \( t \) represents a specific time span, measured in minutes, \( N(t) \) represents the number of commuters in the subway carriage during time \( t \), and \( S(t) \), \( E(t) \), \( I(t) \), and \( R(t) \) represent the number of susceptible, exposed, infected, and recovered individuals present in the carriage during time \( t \), respectively. The variables \( s(t) \), \( e(t) \), \( i(t) \), and \( r(t) \) represent the proportions of these four groups, respectively, in relation to total passenger numbers.

\[
Rs=\frac{ds(t)}{dt} = -\beta i(t)s(t) \quad (3)
\]

\[
Re=\frac{de(t)}{dt} = \beta i(t)s(t) - \sigma e(t) \quad (4)
\]

\[
Ri=\frac{di(t)}{dt} = \sigma e(t) - \gamma i(t) \quad (5)
\]

\[
Rr=\frac{dr(t)}{dt} = \gamma i(t) \quad (6)
\]

Here, \( Rs, Re, Ri, \) and \( Rr \) are differential expressions for the rates of change in the susceptible, exposed, infected, and recovered populations, respectively. The number of exposed individuals within a single environment is positively correlated with \( s(t) \); the proportional coefficient is \( \beta \) (see Eq. (7)). Within \( t \) minutes, the number of people removed from the infected population is proportional to the number of infected people. The proportional coefficient is set to \( \gamma \), and the number of infections removed is \( \gamma i(t) \).

In real life, the infection process occurs only once during a subway journey, and no new recoveries are generated, so the SEIR model is appropriately simplified. Furthermore, exposed individuals do not transmit virus and at the same time do not become reinfected by virus; this group can, therefore, be considered not susceptible to being infected during a subway trip. Therefore, the model may not need to consider the difference in risk of infection between recovered and exposed individuals. The model considers the contact time of susceptible people in different scenarios, contact distance, degree of preventive measures used in a site, and virus transmission capacity. For example, the effects of ventilation and disinfection measures in a confined environment gradually decrease with increasing journey time \( t \). The size of the carriage and the initial number of infected people also affect the infection rate in a confined environment. Setting the number of infected people as \( x \) gives us the following formula:

\[
\beta=\frac{k_i^3xR_0}{dgwv} \quad (7)
\]

Here, \( v \) is the volume of space in the subway carriage and \( k \) is the positive adjustment coefficient, which is defined in combination with different scenarios. According to Eq. (3), the change in the number of susceptible people over time, \( Rs \), is:

\[
Rs=\frac{dS(t)}{dt} = -\beta i(t)s(t) \quad (8)
\]

\[
S(t) = S(0) \exp \left[ -\frac{kxR_0 t^3}{3dgwv} \right] \quad (9)
\]

If the total number of people in the space is fixed, and the number of people infected in time \( t \) is represented by \( I(t) \), we can then obtain the following equation:

\[
I(t) = S(t) - S(0) = S(0) \left\{ 1 - \exp \left[ -\frac{kxR_0 t^3}{3dgwv} \right] \right\} \quad (10)
\]

Equation (10) shows that the increase in the number of infections in a given space is positively correlated with the third power of the contact time between susceptible and infected people. Meanwhile, \( I(t) \) is negatively correlated with the intensity of ventilation, disinfection of the environment, and size of the space.
When the subway train stops at stations, commuters board and alight, thus reorganizing the population in the carriage. Therefore, at every stop a commuter passes through, there will be a change in the people surrounding them. Assuming that the number of passengers getting on and off at subway station \( n \) is \( P_u \) and \( P_d \), respectively, the dynamic change in the number of commuters in the carriage can be defined as follows:

\[
S(n) = S_{n-1} \frac{P_u^n}{P_d^n}
\]  

(11)

In the formula, \( n \) represents the sequence of stations passed through by commuters during one trip, \( P_u^n \) represents the number of people getting on the subway at station \( n \), and \( P_d^n \) represents the number of people getting off the subway at station \( n \). The composition of \( I(t) \) and \( S(t) \) can change dynamically, consistent with the real-life situation.

Finally, the following equation can be obtained:

\[
I(t) = \sum_{i=1}^{n} (S(n) - S(n - 1)) = \sum_{i=1}^{n} S(n) \left\{ 1 - \exp \left[ -\frac{kxR_0 d^3}{3d_{n-1}gwv} \right] \right\}
\]  

(12)

### Results

#### Numerical analysis of parameter changes

The object of this study was to examine the spread of COVID-19. According to the literature (Wu et al. 2020), the primary regeneration number of the SARS-COV-2 virus (\( R_0 \)) has been identified as 2.68. We chose a Xi’an subway train as a model for this study. In order to analyze the impact of changes to the \( k \) value on the risk of infection, \( v \) was taken to be 100, the product \( gw \) was 0.7, and \( d \) (the distance between commuters) was set to 1 m, according to the actual operation of the Xi’an subway. The number of people in one carriage \( S(0) \) was assumed to be 100, and the number of infected people was set to 1. Different \( k \) values were selected to demonstrate how the growth rate of the infected population changes with infection exposure time. The \( k \) values chosen for the numerical simulation of the model were \( 1.0 \times 10^{-6}, 2.0 \times 10^{-6}, 3.0 \times 10^{-6}, 4.0 \times 10^{-6}, \) and \( 5.0 \times 10^{-6} \). The results are shown in Fig. 2a.

Figure 2a shows that the growth trend for the number of infections indicated by the model curve is approximately the same, regardless of the value of \( k \). In other words, the number of infections grows slowly in the first 20 min; however, once contact time exceeds 20 min, the infection rate grows more rapidly, increasing exponentially as contact time increases. Therefore, remaining in the carriage for a longer time increases the risk of infection. This increase in infection risk with increasing journey time has been demonstrated in previous studies (Buonanno et al. 2020a; Chen et al. 2021).

#### Influence of ventilation and disinfection capacity

Disinfection and ventilation at subway stations are particularly important during periods of epidemic prevention and control. These processes affect the magnitude of the \( gw \) value, which in turn affects the risk of infection; a \( gw \) value of 0 indicates that the subway carriage is without ventilation or disinfection facilities. To assess the influence of disinfection and ventilation, the \( k \) value was set as \( 3.0 \times 10^{-4} \), and \( gw \) was varied between 0.2 and 1. The selection of other parameters was consistent with the choices described in the “Numerical analysis of parameter changes” section. Figure 2b shows that the risk of infection changes over time, increasing more rapidly as \( gw \) values are reduced (while other physical parameters remain the same). Thus, for a \( gw \) value of 0.2 and a journey duration of 60 min, the risk of passengers being infected is close to 100%. In contrast, for a \( gw \) value of 1 and a journey time of 60 min, the risk of passengers being infected is approximately 40%. Thus, if the virus-bearing aerosol produced by an infected person cannot be expelled from the carriage quickly enough, the risk of infection increases sharply.

#### Risk of infection at different times of the day

This study used commuters traveling from south to north from Xi’an’s DYT station as the basis for the model. In
Fig. 1, we can see that commuters on line 4 can transfer to other lines at stations WLK and XZZX; there will also be transfers from other lines to line 4. This results in a change in the commuter environment (crowding). Figure 6 (Appendix) gives the percentage of transfer commuters counted throughout the subway AFC system.

In order to study the risk of COVID-19 infection on the subway at different times, three weekday time periods were studied: morning peak, evening peak, and common peak periods. According to a previous study on subway travel in Xi’an, the morning peak hours last from 8:30 to 9:00, the evening peak hours are from 17:30 to 18:00, and the weekday common peak hours are from 13:30 to 14:00 (Yu et al. 2020). In the calculation process, we chose a $k$ value of $3 \times 10^{-4}$ and an $S(0)$ value of 100 people. The values of $v$, $gw$, and $d$ were set to 100, 0.7, and 1, respectively (Zhang et al. 2018).

Overall, Fig. 3 indicates that the chance of being infected increases with journey duration in every period. Specifically, consistent with Eq. (12), the risk of passenger infection is cumulative over time. Passengers boarding and alighting at each subway stop cause a change in physical environment factors due to the changing numbers of passengers in the carriage; thus, different rates of infection are produced for the same journey time during the three periods. For all three periods, the rate of growth appears relatively stable until journey duration reaches 25 min; however, after 25 min, the risk of infection increases more rapidly and is no longer proportional to ride duration.

Compared to infection rates in the morning and common peak periods, the infection rate in the evening peak increases more rapidly as ride duration increases. For trains departing from DYT station and traveling from south to north, there are more outbound passengers than inbound passengers during the first 25 min. This results in a larger average distance between passengers, compared with during the morning and common peak periods; in turn, this results in a lower infection rate for passengers in the first 25 min of the evening peak, compared with the other two periods. However, the risk of infection then increases more steeply after 25 min due to greater numbers of passengers entering the train at subsequent subway stations during the evening peak than during the other two periods, reducing the average distance between commuters. However, overall, regardless of the period, infection rates start to increase more rapidly as journey duration approaches 25 min.

**Influence of average commuter spacing on the risk of infection**

To compare how the average distance between commuters in the carriage affects infection rates, we set the journey time for the model at 20 min. The remaining parameters were selected as described above for different time periods. The effect of average commuter spacing on infection risk is represented in Fig. 4.

From Fig. 4, it can be seen that the infection rate decreases sharply as $d$ increases. However, above a certain threshold, overall risk declines only slightly as $d$ values increase, consistent with public perceptions. The risk of infection decreases at the highest rate between...
0.1 and 0.5 m. In contrast, when the distance between commuters increases from 0.6 to 1 m, the infection rate only drops by a further one-third. It has also been shown that the maintenance of social distance plays an essential role in preventing COVID-19 outbreaks and that a customary social distance of 1.5 m or more should be maintained (Bourouiba 2020). It has also been suggested that 1.5 m is a critical threshold: contact with airborne droplets by susceptible humans within approximately 1.5 m of the source of infection results in a higher chance of viral infection (Faridi et al. 2020; Liu et al. 2017).

Discussion

According to the COVID-19 transmission model and case studies described in this paper, many factors affect the risk of COVID-19 infections among commuters traveling by subway. Average distance between commuters, levels of ventilation and disinfection, and time spent on each journey are all important factors (Bourouiba 2020; Miller et al. 2022). Studies have shown that droplets containing the COVID-19 virus can remain in a confined space for a relatively long time (Buonanno et al. 2020b; Mizumoto and Chowell 2020); furthermore, increased proximity to a source of infection increases the risk of contracting the disease. This means that maintaining social distance can effectively reduce the risk of infection. Previous studies have suggested that droplets from an infected person’s cough can spread up to 6 m indoors when the size and humidity of the space are favorable for transmission (Liu et al. 2017; WHO 2014).

The average person-to-person distance of commuters riding the subway is not subjectively controlled by individuals. At the beginning of the COVID-19 outbreak in China, the number of subway carriages running was increased, and there was also a steep drop in passenger numbers due to efforts to interrupt the spread of the epidemic. However, in the post-epidemic era, productivity and social life are gradually returning to normal. This requires subway managers to organize their operations to minimize the risk of commuter infections. The ability to ventilate and disinfect a carriage greatly affects the risk of COVID-19 infection; therefore, high ventilation rates are an important means of reducing the risk of infection (Moreno et al. 2021).

This study attempts to consider the risk of COVID-19 infection in susceptible individuals by simultaneously considering the ventilation and disinfection capacity of the subway car, average commuter spacing, dynamic changes in commuter onboarding and offboarding, and commuting time of commuters per subway journey. Using the DYT station in Xi’an as a case study, it was shown that the infection rate increased more slowly for journeys of less than 25 min. At the same time, the evening peak caused a rapid increase in the risk of infection due to a surge in commuter traffic. Therefore, increasing the average distance between commuters and improving ventilation and disinfection are the most important measures that subway operation managers can take to help decrease the spread of the virus.

However, it should be noted that this study also has some limitations. Firstly, the ability of the virus to spread is gradually changing as it acquires mutations. For example, the SARS-CoV-2
Delta mutation (variant of concern) is strongly transmissible and is gradually becoming the primary variant in the post-epidemic era (Williams et al. 2021). Secondly, due to inconsistencies in regulations worldwide, it is not always mandatory for the public to wear masks when traveling on public transportation. Furthermore, due to variation in the ability of different types of masks to block viruses, the effect of masks could not be included in this study (Faridi et al. 2020; Liu et al. 2017; Mathai et al. 2021). This model is intended to compare the risk of possible infection for commuters during normal operation. Thirdly, this study did not consider the differences in infection risk due to the variation in air flow around passengers in the subway carriages. Finally, for feasibility of calculation, our model assumed a consistent average commuter distance; however, this was not equivalent to the real-world average distance.

Conclusion

During the post-COVID-19 period, although the population has become less fearful than during the pandemic, the continuing confrontation with COVID-19 is an inevitable source of anxiety. To this end, this paper evaluated the risk of possible COVID-19 infection in commuters traveling by subway and proposed a number of meaningful conclusions. Firstly, the improvement of the outbreak transmission-based SEIR model proposed in this study meant that it could be applied effectively to the assessment of COVID-19 infection risk in subway passenger carriages. Secondly, according to our model, the risk of being infected by COVID-19 depended on the time of day, correlating with passenger flow. Thirdly, the risk of COVID-19 infection increased exponentially as journey time increased, even with proper prevention and control measures. Finally, these results indicate that subway operators should increase the average distance between passengers as much as possible. This study concluded that an average social spacing of at least 1 m needs to be maintained.

Even though this study analyzed the risk of COVID-19 infection for subway users throughout their journey, future research efforts are required to improve a number of aspects. To begin with, the ability of the virus to propagate in air is uncertain and complex, varying over time. Moreover, future research should also consider the survival of viruses under various conditions, as well as the impact of the protective effects of masks on the results of the model, in order to increase the accuracy of the results.

In the face of the next pandemic crisis, policymakers must develop safer and more effective transport management policies. In addition, prevention and control of the epidemic require more active efforts from all sectors of society, including increased vaccine development and vaccination efforts, strict entry quarantine, and other preventive measures. These measures will be essential prerequisites for ensuring safety and promoting active travel.

Appendix

Fig. 5 Xi’an subway passenger flow change and control policy time distribution in 2020
Author contribution Conceptualization, P.L.; methodology, P.L.; software, X.C.; validation, C.Z.; formal analysis, C.Z. and C.M.; writing—review and editing, X.C.; visualization, C.M.; funding acquisition, C.M.; investigation, W.L.; resources, C.M.; data curation, W.L.; writing—original draft preparation, P.L.

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Data availability The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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