Interactive effects between travel behaviour and COVID-19: a questionnaire study

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Abstract

This study has two main objectives: (i) to analyse the effect of travel characteristics on the spreading of disease, and (ii) to determine the effect of COVID-19 on travel behaviour at the individual level. First, the study analyses the effect of passenger volume and the proportions of different modes of travel on the spread of COVID-19 in the early stage. The developed spatial autoregressive model shows that total passenger volume and proportions of air and railway passenger volumes are positively associated with the cumulative confirmed cases. Second, a questionnaire is analysed to determine changes in travel behaviour after COVID-19. The results indicate that the number of total trips considerably decreased. Public transport usage decreased by 20.5%, while private car usage increased by 6.4%. Then the factors affecting the changes in travel behaviour are analysed by logit models. The findings reveal significant factors, including gender, occupation and travel restriction. It is expected that the findings from this study would be helpful for management and control of traffic during a pandemic.

Keywords: COVID-19; transportation system; questionnaire survey; disease spread; pandemic

1. Background

Since the first case of COVID-19 was confirmed in December 2019, it has been rapidly spreading worldwide. More than 88 million people have been infected as of 8 January 2021. It remains a threat to public health around the world and has a serious impact on the economic development, transportation development and social stability of various countries, as well as causing other huge losses. Transport systems play a vital role in spreading infectious diseases. Furthermore, the pandemic has a tremendous impact on transport. This study focuses on two main objectives. The first one is to explore effects of travel...
characteristics of a region on the spread of COVID-19 in the early stage. The second one is to study effects of the outbreak of COVID-19 on travel behaviour, comparing the number of trips and travel modes before and after the pandemic.

2. Literature review

Tatem et al. [1] briefly reviewed important events of infectious diseases and vector movements, and then outlined potential approaches for future research on infectious disease campaigns, focusing on vector invasion and vector-borne disease input. Pathogens and their vectors can move further and faster than ever before because air, sea and land transport networks continue to expand in reach, speed of travel and volume of passengers and goods carried. Li and Ma [2] showed that the rapid development in transport infrastructure and the liberalization of migration restrictions in the recent decades had contributed to around 24% of the infections outside of Hubei province. Budd and Ison [3] investigated the association between changes in traffic volume and the spread of COVID-19, which indicated that the heavier traffic, the greater contact people are, and the greater risk of infection in turn. Due to the high speed of aircraft, one can reach almost anywhere in a day. Hence, the air passenger volume plays a prominent role in the spread of the disease. Colizza et al. [4] stated that the air-transport-network properties are responsible for the global pattern of emerging disease. Laua et al. [5] analysed the association between air traffic and the COVID-19 outbreak. The results show that the total number of COVID-19 cases by regions in China has a strong linear relationship with passenger volume. Pequeno et al. [6] also found that the number of confirmed cases was mainly related to the number of arriving flights and population density, increasing with both factors. They also found that the disease is sensitive to temperature. Cheng [7] chose to build an artificial transport system to study the impact of traffic on the spread of infectious diseases. Wet climates accelerate the spread of human plague. Xu et al. [8] found that the presence of major roads, rivers and coastline accelerates the spread of diseases and shapes transmission patterns.

Since the outbreak of COVID-19, the world has drastically changed, including mobility and transport. Sun et al. [9] compared the aviation network before and after COVID-19 based on a multi-granularity network analysis, at different scales, ranging from worldwide airport networks, to international country networks, and to domestic airport networks for representative countries/regions. Their study found each airport lost 50% of its connections on average. Mogaji [10] studied the present and long-term impact of COVID-19 on transport in Lagos State, Nigeria. Brough et al. [11] analysed the data on travel volumes, modes, and preferences for different demographic groups. Loske [12] proved that the increasing freight volume for dry products in retail logistics depend on the strength quantified through the total number of new infections per day. De Vos [13] found that walking and cycling, recreationally or utilitarian, could be important ways to maintain satisfactory levels of health and well-being. The author discussed the implications of social distancing on travel patterns. The study focused on the effect of social distancing on subjective well-being and health status. Frank et al. [14] estimated the variability of people to engage in remote work and social distancing. Alejandro and Oded [15] identified the research needs and outlines measures to reduce crowding in public transport. Zhou et al. [16] proposed routines and practical pandemic prevention strategies for urban public transport system from three aspects: infectious source, transmission route and susceptible population of COVID-19. In addition, Mogaji [10] stressed the role of the individual as a responsible autonomous actor in delivering socially desired transport outcomes. Shamshiripour et al. [17] also investigated how travel behaviours had changed during the COVID-19 pandemic. They focused on the economically vulnerable groups and the dynamics of working from home. In addition, Paradya et al. [18] developed three models separately, pooled OLS, random-effect model and first-difference regression, to estimated going-out frequency. Changes in the characteristics of taxi trips at different periods were analysed by Nian et al. [19], and a sharp drop of the number of taxi trips was found.

Although many studies have explored the effects of a pandemic on travel, there are still several research gaps. First, no study has explored the traffic volume and proportion of different travel modes that affecting the development and severity of COVID-19. Second, the changes in travel behaviour and willingness to take public transport for the whole groups in society has not been studied. In addition, no study has investigated the individual factors affecting the changes
in travel behaviour. Therefore, this study aims at exploring the interactive effects between the pandemic and travel behaviour, namely, the effect of the volume of passengers on COVID-19 spreads, as shown in Equation (1), and the effect of COVID-19 on travel behaviour at the individual level using the data from a questionnaire, and shown in Equation (2).

3. Effect of travel characteristics on the spread of COVID-19

The first analysis is to explore effect of travel on the spread of COVID-19 in the early stage. In the analysis, it was presumed that the number of trips and their characteristics of 2019 had significant influences on the spread before the travel restriction policy imposed in late January 2020. Thus, the travel data of 2019 and the new confirmed cases in January were collected. A spatial model was developed to identify how travel characteristics of the provinces affect the spread of COVID-19.

3.1 Data collection

3.1.1 Data on new confirmed cases. Residents’ travel was restricted in China during the serious period of COVID-19, due to the implementation of Level 1 Response to Major Public Health Emergency on 23 January 2020. Therefore, there were few passenger journeys after 23 January 2020. However, the cases confirmed during 23–31 January 2020 are assumed to be related to their travel before 23 January 2020. In this analysis, it is hypothesized that new confirmed cases in January 2020 are influenced by the annual passenger volume in 2019.

There are 13 332 temporarily confirmed cases before 12 February 2020, which are not included in COVID-19 confirmed cases. However, temporarily confirmed cases was added to the new confirmed cases in Hubei Province on 12 February 2020. Therefore, in this study, the 13 332 temporarily confirmed cases were assigned to the cases prior to 12 February 2020, based on the weight. The formula is as follows:

$$a'_t = \frac{a_t}{\sum_{t=1}^T a_t} \cdot A$$  \hspace{1cm} (1)

where $a'_t$ denotes the corrected number of new cases on day $t$, $a_t$ denotes the number of new cases on day $t$, $T$ denotes the number of days before 12 February and $A$ denotes the total number of temporarily confirmed cases before 12 February. The cumulative number of confirmed cases of each province in January is shown in Fig. 1.

3.1.2 Data on passenger volume. The data on passenger volume by province in China is from the China Statistical Yearbook 2020. Detailed data on the annual passenger volume by province (excluding Taiwan, Hong Kong and Macao) in 2019 is shown in Fig. 2. The differences in passenger volume among provinces are very large. The passenger volume in Guangdong in 2019 was 1 500 million, while it was less than 20 million in Tibet Autonomous Region, China.
The passenger volume is divided into four by mode: rail, road, waterway and air. As it is expected that the effects of each mode are different, their effects were separately analysed. Fig. 3 presents the percentages of four types of passenger volume in each province. It shows that highway is the most frequently used mode in most provinces except for Shanghai. Shanghai has very different characteristics in the travel mode composition. In Shanghai, highway travel accounts for only 14%, whereas rail and air travel for 57% and 27%, respectively.

Table 1 summarizes the descriptive statistics of all the variables. The number of cumulative confirmed cases in Hubei until 31 January 2020 was the largest, with 10 195 confirmed cases. Conversely, there was only 1 confirmed case in Tibet until 31 January 2020. In terms of travel volume, the difference between the minimum and maximum of total journeys is significantly large. The provinces with the largest and smallest total journeys are Guangdong and Tibet, respectively. The proportion of highway travel is the largest (70.1%) and followed by the railway (22.7%). The proportions of water and air travel are relatively small (1.6% and 5.7%, respectively).

### 3.2 Modelling confirmed cases

Considering the influence of spatial location on pandemic situation, a spatial autoregressive (SAR) model was used to study the relationship between
### Table 1. Descriptive statistics

| Variable                                           | Mean    | SD       | Min.   | Max.   |
|----------------------------------------------------|---------|----------|--------|--------|
| Cumulative confirmed cases until January 2020      | 477.729 | 10 809.818 | 1      | 10 195 |
| Population (million)                               | 45.285  | 2912.45  | 350.6  | 115.21 |
| Average GDP (yuan)                                 | 32 698.435 | 32 994.56  | 16 523 | 1 499 777 |
| Total journeys (million)                           | 568.392 | 38 263.232 | 15 623 | 1 499 777 |
| Proportion of railway travel                       | 0.227   | 0.097    | 0.076  | 0.570  |
| Proportion of highway travel                       | 0.701   | 0.136    | 0.141  | 0.884  |
| Proportion of water travel                         | 0.016   | 0.020    | 0.000  | 0.106  |
| Proportion of air travel                           | 0.057   | 0.055    | 0.013  | 0.270  |

confirmed cases and traffic. The SAR model is

\[
y = \beta_0 + \rho W y + X \beta + \gamma WX + U
\]

\[
U = \lambda W U + \varepsilon
\]

(2)

In both equations, the bold variables and parameters indicate that they are vectors. \(X\) and \(y\) are an independent variable vector and a dependent variable vector, respectively. \(W\) is a spatial weight matrix. \(\beta, \gamma, \lambda\) are parameters and \(\varepsilon\) is a random error term following normal distribution.

In general, the pandemic situations in two provinces adjacent to or close to each other are similar. Therefore, a spatial weight matrix \(W\) is included in the SAR model to represent the influence of spatial location. There are two kinds of spatial weight matrix: adjacency matrix and inverse distance matrix. Adjacency matrix is a matrix that represents the adjacency relationship between nodes, where 1 denotes that the two nodes are adjacent while 0 denotes they are not. The inverse distance matrix shows the inverse distance between any two nodes, with the following form:

\[
\begin{pmatrix}
0 & \cdots & (d_{1j})^{-k} \\
\vdots & \ddots & \vdots \\
(d_{i1})^{-k} & \cdots & 0
\end{pmatrix}
\]

where \(d_{ij}\) (\(i \neq j\)) denotes the distance between nodes \(i\) and nodes \(j\), \(-k\) denotes the power of \(d_{ij}\) and \(k = 1\). The smaller the value of \(d_{ij}\), the stronger the connection between the two nodes. If \(i = j\), \((d_{ij})^{-k} = 0\) is defined.

Since the economic and population centre of a province is its provincial capital, the nodes in the spatial weight matrix are the provincial capital of each province, instead of its geometric centre. In addition, the geometric centre of Inner Mongolia is not in China, which is another reason why the geometric centres were not chosen as the reference locations. The distance between two provinces can be calculated by the longitude and latitude coordinates of their provincial capitals. The dependent variable in the model is the cumulative number of confirmed cases in each province and the independent variables are the total volume of passenger, proportion of each type of passenger volume. It is worth noting that the number of confirmed cases in Hubei is particularly high. Hence, a dummy variable for Hubei was included to control its extremely large number of confirmed cases.

There are two methods to resolve the SAR model: maximum likelihood estimation (MLE) and generalized space two stage least squares method (GS2SLS). The results of the two methods are essentially the same and the former (GS2SLS) was used to resolve the SAR model in this study. Firstly, all the independent variables were put into the model, and then the insignificant variables were eliminated one by one. Eventually, only four independent variables: Hubei, total journeys, percentage of railway passengers and percentage of air passengers, are significant. The results are illustrated in Table 2.

Table 2 shows the developed SAR model. The model indicates that Hubei, total travel, proportions of rail and air travel, and three spatial effects (i.e., total journeys, proportion of air travel, and cumulative confirmed cases) are statistically significantly associated with the number of cumulative confirmed cases. In addition, the coefficient of percentage of air travel is 928.500, indicating that if the percentage of air increases by 10%, the cumulative cases would increase by 92.85, ceteris paribus. The coefficient of percentage of air passengers is ten times larger than that of the railway, which indicates that the air transport has higher effects than railway on the spread of COVID-19. The coefficient of determination \((R^2)\) in the model is 0.9982, indicating that the prediction results in most provinces are good and the differences
Table 2. Results of the SAR model

| Variable                      | Coefficient | SE    | p    |
|-------------------------------|-------------|-------|------|
| Hubei                         | 10 213.580  | 85.047| 0.000|
| Total journeys                | 0.301       | 0.032 | 0.000|
| Proportion of railway travel  | 191.621     | 76.648| 0.012|
| Proportion of air travel      | 928.500     | 223.492| 0.000|
| Intercept                     | −172.947    | 28.933| 0.000|
| Total travel                  | −0.176      | 0.070 | 0.012|
| Proportion of air travel      | 1075.130    | 600.318| 0.073|
| Cumulative confirmed cases (dependent variable) | 0.117 | 0.021 | 0.000|
| Spatial error                 | −1.761      | 4.646 | 0.705|

Mean absolute error = 50.54; root mean squared error = 74.74 R² = 0.9982, Wald test of spatial terms: $\chi^2(4) = 55.75$ ($p < 0.0001$)

of the predicted data and actual data are very small. Also, Wald test of spatial terms confirms that adopting an SAR model for the data is reasonable.

The comparison of actual values to predicted values is presented in Fig. 4.

4 Effect of the spread of COVID-19 on travel behaviour

The second analysis is to investigate the effect of the spread of COVID-19 on the travel behaviour of residents in China. With this goal, a questionnaire on the travel behaviour during the period of COVID-19 was designed and distributed online.

4.1 Residential travel surveys before and after the outbreak

The purpose of this survey is to study and analyse the changes in the travel behaviour of Chinese residents before and after COVID-19. The respondents consist of different genders, age groups and regions in China. Due to the impact of the pandemic and the large scope of the survey, the questionnaire was conducted online, using an online questionnaire platform. A total of 774 questionnaires were returned, and after eliminating invalid questionnaires, 531 valid questionnaires were finally obtained. The basic information of the respondents to this online questionnaire is summarized in Table 3.

Table 3 shows that 233 of the respondents in this survey are male and 298 are female, accounting for 44% and 56%, respectively. The age distribution of the survey respondents shows that the largest proportion of respondents are between 18 and 24 years old, accounting for 36%. The two oldest age groups (55–64 years old and over 65 years old) and the youngest age group (under 18 years old) occupy small proportions, only 8%, 10% and 10%, respectively. According to the survey, the number of households with one car is 307, accounting for more than half of all survey respondents, followed by 115 households without cars, accounting for 21.7%. The proportion of households with two or more cars is few. Table 3 shows that most of the survey respondents are in families with three or four members, accounting for 67.4% of the total. The proportion of households with annual income less than 50 000 Chinese Yuan and between 50 000 and 65 000 Chinese Yuan are the largest.

4.1.1 Residents’ perception of and attitude towards the pandemic situation. Fig. 5 shows residents’ perception of the pandemic. According to the results of the survey, 306 of respondents thought this pandemic was very serious, accounting for 57.63%, and 186 of respondents thought the pandemic was serious, accounting for 35.03%. Few people thought the pandemic was not very serious or not serious at all, only accounting for less than 2%. In addition, the attitudes of responders also were investigated in the questionnaire.

Fig. 6 exhibits the attitudes of residents towards reducing travel during the pandemic. Among them, 380 respondents thought it was very necessary to reduce travel during the pandemic, accounting for 71.56%, while the number of people who considered this very unnecessary is 20, accounting for only 3.77%.

4.1.2 Changes in the number of trips made by residents. Under the influence of COVID-19, the national pandemic prevention and control response was initiated. The travel of residents was restricted after the implementation of Level 1
Response to Major Public Health Emergency on 23 January 2020. Our study investigated the changes in the number of trips per week before and after the pandemic outbreak.

Fig. 7 illustrates that after the outbreak of the pandemic, the number of trips made by residents decreased significantly. The largest proportions are the residents who made no trips and those who made 1–3 trips (238 respondents and 174 respondents, respectively). While before the outbreak of the pandemic, the largest proportion is the residents who made more than 10 trips. A chi-square test showed that there is a significant difference in the number of trips made by residents before and after the pandemic ($\chi^2(4) = 345.44, p < 0.001$).

4.1.3 Changes in modes of transport of residents. Resident’s travel modes are also influenced by COVID-19, and the modes of travel chosen by respondents before and after the pandemic are shown in Figs 8 and 9. Comparing the two graphs, the proportions of residents who walk most often and those who use public transport
Table 3. Individual information of respondents (n = 531)

| Variable                        | Category         | Number |
|---------------------------------|------------------|--------|
| Gender                          | Male             | 233    |
|                                 | Female           | 298    |
| Age                             | Under 18         | 52     |
|                                 | 18–24            | 193    |
|                                 | 25–34            | 101    |
|                                 | 35–54            | 90     |
|                                 | 55–64            | 43     |
|                                 | Over 65          | 52     |
|                                 | 0                | 115    |
|                                 | 1                | 307    |
| Number of family vehicles       | 2                | 93     |
|                                 | 3                | 14     |
|                                 | 4                | 2      |
|                                 | 1                | 4      |
|                                 | 2                | 19     |
|                                 | 3                | 185    |
|                                 | 4                | 173    |
|                                 | 5                | 83     |
|                                 | >5               | 67     |
|                                 | Under 50 000     | 187    |
|                                 | 50 000–65 000    | 105    |
|                                 | 65 000–80 000    | 77     |
|                                 | 80 000–120 000   | 91     |
|                                 | 120 000–200 000  | 38     |
|                                 | Over 200 000     | 33     |

Fig. 5. Respondents’ perception of the severity of the pandemic

Fig. 6. Respondents’ attitude towards the necessity of reducing travel
Fig. 7. Number of trips made by residents before and after the outbreak

Fig. 8. Percentage of travel modes of residents before outbreak

Fig. 9. Percentage of travel modes of residents after outbreak
most often change the most. After the outbreak of the pandemic, the proportion of residents who travel on foot increased by 23.73%, while the proportion of residents who travel by public transport decreased by 20.53%, compared with pre-pandemic period. The decrease was caused by the fact that residents were reluctant to travel by bus and subway to avoid cross-infection. In contrast, taking private cars makes it less probable for people to come into contact with those infected with COVID-19, so during the pandemic, the proportion of residents who travel by private cars increased by 6.4%.

The chi-square test results of travel modes before and after the outbreak of the pandemic, and COVID-19 has an important effect on the choice of travel mode.

4.2 Forecast analysis of residents’ trips
4.2.1 Changes in the number of trips. A variable, the changes in the number of trips before and after the pandemic, was added in this study. It is equal to the number of trips before the pandemic minus the number of trips after pandemic. A linear function was developed, where the change in the number of trips is the dependent variable. The first category of each variable (see Table 3) is the base group. First, all the independent variables were put into the model and then the insignificant variables were eliminated one by one.

Table 4. Linear model for the change in the number of trips

| Variables                      | Coefficient | SE   | t     | p      |
|--------------------------------|-------------|------|-------|--------|
| Constant                       | 1.478       | 0.1025 | −14.42 | <0.001 |
| Gender: female (vs male)       | 0.244       | 0.1101 | −2.22  | 0.027  |
| Student (vs non-student)       | 1.790       | 0.110  | −1.63  | 0.104  |
| Travel restriction: no (vs yes)| −0.534      | 0.118  | 4.51   | <0.001 |

\(F(3, 527) = 9.350 (p < 0.001)\); root mean squared error = 1.260.

Table 5. Logit model for the changes in the trip mode

| Variables                      | Coefficient | SE   | z     | p      |
|--------------------------------|-------------|------|-------|--------|
| Constant                       | 0.291       | 0.154 | 1.89  | 0.059  |
| Gender: female (vs male)       | 0.288       | 0.177 | 1.62  | 0.105  |
| Student (vs non-student)       | −0.407      | 0.219 | −1.86 | 0.063  |
| Travel restriction: no (vs yes)| −0.363      | 0.192 | −1.89 | 0.059  |

Log-likelihood = −359.1125; pseudo \(R^2 = 0.013 \); \(\chi^2(3) = 9.40 \) (\(p = 0.025\)).

Table 6. Logit model for whether the respondent’s main mode is personal car after the pandemic

| Variables                      | Coefficient | SE   | z     | p      |
|--------------------------------|-------------|------|-------|--------|
| Constant                       | −0.824      | 0.196 | −4.17 | <0.001 |
| Annual income of household:    |             |      |       |        |
| >80 000 yuan (vs ≤80 000 yuan) | 0.818       | 0.212 | 3.86  | <0.001 |
| Number of family members:      |             |      |       |        |
| 3 or more (vs less than 3)     | −0.538      | 0.209 | −2.58 | 0.010  |
| Car ownership:                 |             |      |       |        |
| Have car (vs no cars)          | 0.903       | 0.239 | 3.77  | <0.001 |
| Student (vs non-student)       | −0.598      | 0.209 | −2.86 | 0.004  |

Log-likelihood = −293.671; pseudo \(R^2 = 0.084 \); \(\chi^2(4) = 53.94 \) (\(p < 0.001\)).

Table 7. Logit model for the change in willingness to purchase a new vehicle

| Variables                      | Coefficient | SE   | z     | p      |
|--------------------------------|-------------|------|-------|--------|
| Constant                       | −1.549      | 0.176 | −8.79 | <0.001 |
| Student (vs non-student)       | −0.542      | 0.277 | −1.96 | 0.051  |
| Travel restriction: no (vs yes)| −0.684      | 0.325 | −2.10 | 0.035  |

Log-likelihood = −196.816; pseudo \(R^2 = 0.012 \); \(\chi^2(2) = 8.92 \) (\(p = 0.022\)).
one. Eventually, only three independent variables: gender, whether student or not and travel restriction, were retained. The results are shown in Table 4.

The model results are presented in Table 4. The coefficient for females is –0.244, indicating that the change in the number of trips for females is more than that for males. Similarly, the reduction in trips is more significant for students than for non-students, and reduction in trips is more significant for residents when trips are restricted than when they are not.

4.2.2 Changes in trip modes. As discussed above, the trip modes of residents before and after the pandemic are significantly different. Therefore, a binary logit regression model was used to predict whether the trip modes of residents changed after the pandemic. The dependent variable here is whether travel modes changed after the pandemic occurred. The independent variables were filtered and finally we retained three variables: gender, number of cars owned and travel restriction.

The significance level of 0.15 was applied in the analysis to secure more significant variables. The estimates of parameters are shown in Table 5, which shows that female residents are more likely to change their modes of trip after pandemic than males, residents who own more than one car are less likely to change their modes of trip than residents owning one or no car. One will be less likely to change his/her mode of trip when travel is restricted than when it is not.

Another binary logit model was built to analyse who are more likely to use personal car after the outbreak (Table 6). The results show that the one whose family with higher income, less family members and more cars are more likely to travel by private cars after COVID-19.

4.2.3 Changes in willingness to purchase a new vehicle. We built a binary logit model to predict whether residents changed their willingness to purchase a new vehicle after the pandemic. The dependent variable denoted by $Y_4$, where $Y_4 = \begin{cases} 1, & \text{yes} \\ 0, & \text{no} \end{cases}$. The independent variables were filtered and finally we retained two variables: whether student or not, travel restriction. A logit model was developed, and the result is shown in Table 7.

It can be seen in Table 7, the coefficient of student is –0.542, indicating that a student is less willing to purchase a vehicle. Similarly, a person whose community restricts travel during the pandemic is more likely to change his/her willing to purchase a new vehicle. Based on the logit model, the change in their willingness to purchase a new vehicle were predicted and compared with the actual data. The overall percentage of correct predictions is 87.4%.

5 Conclusions
The first part in the study explored the effect of travel characteristic on the spread of COVID-19 by provinces in China with an SAR model. The second part investigated the changes of travel behaviour after outbreak of COVID-19 and the relationship between the changes in travel behaviour and personal characteristics based on a questionnaire in China. The key findings of this study are as follows:

The current study offers useful and practical information for the government to take measures to efficiently control the current situation and also when a new pandemic breaks out. This study also investigated the changes of travel behaviour during the pandemic, which is expected to be useful for transport sector to manage and control existing travel behaviours. In the future, the study’s scope can be expanded to global level to explore the development of the pandemic in other countries. In addition, we only considered the travel intra-city when studying the impact of the pandemic development on the travel behaviour in this study. Future research can take long-distance travel into account and study the effect of the pandemic on cross-city travel.

Supplementary data
Supplementary data is available at Transportation Safety and Environment online.

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Author contribution statement

The authors confirm that the contributions to the paper were as follows: study conception and design: Jinbao Zhang and Jaeyoung Lee; data collection: Jinbao Zhang; analysis and interpretation of results: Jinbao Zhang and Jaeyoung Lee; draft manuscript preparation: Jinbao Zhang and Jaeyoung Lee. All authors reviewed the results and approved the final version of the manuscript.

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