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Influence of perceived risk on travel mode choice during Covid-19

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ABSTRACT

We aim to understand the effect of different information types on risk perception and examine the relationship between perceived risk and travel behaviour during a pandemic outbreak. A hybrid choice model structure, incorporating a multiple discrete-continuous extreme value model, was formulated and estimated to explore travellers' mode choice and usage changes. We used a risk perception map to visually explain which risk elements felt unfamiliar and uncontrollable to travellers. *Virus variation*, *Potential sequelae*, and *Long-term coexistence of coronavirus with humans* were perceived as the most unfamiliar and uncontrollable risk elements. The model results indicate that increased perceived risk tends to reduce travellers' use of public transport and increase the use of shared bikes and private cars. Reducing passengers' perceived risk is critical to encourage the re-uptake of public transport in the post-pandemic era. As travellers also show significant heterogeneity, governments should aim to design targeted intervention strategies to encourage different travellers to return to public transport when considering risk communication.

1. Introduction

The Covid-19 pandemic significantly impacted people's lives worldwide, including an overall reduction in daily travel and out-of-home activities (Hess et al., 2022; Vickerman, 2021; Currie et al., 2021). Further, as some travel modes (i.e., subway, bus, and other forms of public transport) provide a riskier environment to travellers due to more prolonged exposure in a limited space without social distancing, travellers tend to shift to 'safer' modes as a preventive measure. In fact, since the inception of the pandemic, public transport (PT) and shared transport modes have experienced a significant decrease in ridership while active travel was on the rise (Marra et al., 2022; Liu et al., 2022; Meister et al., 2022; Zhao and Gao, 2022; Hensher et al., 2021; Pawar et al., 2021; Tirachini and Cats, 2020). These effects were caused partly by restrictive government or operator measures (e.g., reduced capacity to enable social distancing). However, part has also been attributed to the perceived risks by travellers and voluntary modal shifts.

Risk perceptions are closely related to risk aversion behaviour and are central to health-related behavioural theories (Slovic, 1987). These theories posit that potential health-specific dangers motivate people to change their previous habitual behaviour. Studies have examined that in many hazard contexts faced with health threats, travellers may change their travel behaviour (Cahyanto et al., 2016; Leggat et al., 2010; Floyd et al., 2000). While there are numerous recent studies on how travellers change their transport mode to reduce the risk of infection during Covid-19 (Christidis et al., 2022; Vallejo-Borda et al., 2023; Villacé-Molinero et al., 2021; Parady et al., 2020), none have explored in detail the role of perceived risk on behaviour changes.

Further, since the inception of Covid-19, travellers have been receiving positive and negative information, both public transport-specific (e.g., reports of infection cases and about protection measures adopted in public transport systems, and so on) as well as generic (e.g., information about the effectiveness of masks, vaccines), which has affected their perceptions of risk. Studies in psychology have highlighted the critical role of risk communication during a hazard to ensure an appropriate response (Naveen and Gurtoo, 2022; Chatterjee et al., 2020; Abrams and Greenhawt, 2020; DiClemente and Jackson, 2016). Therefore, understanding the public's perception of risk elements is essential

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for designing an appropriate risk communication strategy (Slovic, 1987). Otherwise, well-intended risk communication may be ineffective, such as the misuse of an exaggerated 'War state' to describe the pandemic by some Chinese cities in the early stages of Covid-19, which caused some panic among the public.[1] Thus, given the dynamic nature of Covid-19, where the emergence of new variants and new scientific findings lead to continuous changes in travellers' perceptions, policymakers need to have a good understanding of how to update risk communication strategies, particularly for campaigns aimed at promoting the re-uptake of public transport. On the other hand, we have not found thorough studies on the travellers' perceptions of different elements related to the risk of infection during the pandemic (e.g., chances of getting the virus in different modes, the severity of the infection, and the vaccine's effectiveness). Also, we have not found discussions on the impacts of different risk communication strategies on travellers in the transport context.

To fill these gaps, this study considers the effect of different types of information about risk perceptions and how the perceived risk correlates with travel behavioural changes during Covid-19. The focus is on modelling changes in mode choice and travel frequency over time, and on formulating appropriate risk communication strategies that may eliminate or reduce misperceptions among travellers, encouraging them to use public transport when it is safe.

Our approach considers first scaling and then presenting visually, to a sample of travellers, the perceived risks of different infection elements on a risk perception map from two aspects: *knowledge* and *control* (Slovic, 1987). The approach allows for a more unambiguous interpretation and understanding of the key factors driving the perceived risk of different modes. Secondly, we collected revealed preference (RP) travel data from this sample before and during Covid-19. Thirdly, we used these data to formulate a hybrid choice model structure, incorporating a multiple indicator multiple cause (MIMIC) model (Bollen, 1989) and a multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2005, 2008) for estimating the individuals' change of travel mode and travel frequency jointly.

We used the scaled *knowledge* and *control* measurements as indicators of travellers' perceived risks in the model. The emphasis here was on the perceived risk of using public transport, implemented in the MIMIC model component, as a shift from public transport to private modes (i.e., the most substantial and widely observed change). The impact on public transport usage is key from a policy perspective, as governments were interested in limiting travellers' use of public transport during the pandemic (Gkiotsalitis and Cats, 2021). Thus, although we discussed the latent constructs related to other modes in the risk perception map activity, the modelling part focused on latent variables related to the choice of public transport.

The rest of the paper is structured as follows: Section 2 provides an overview of the literature review and introduces the hypotheses of our study. In Section 3, we describe the study design and methodology, including details on data collection, variable introduction, and model construction. Section 4 presents the results, while Section 5 discusses the implications of our findings. Finally, in Section 6, we outline possible directions for future research.

2. Literature review

2.1. Risk perception and behaviour

Risk perception can be interpreted as a subjective assessment of a threat scenario based on its characteristics and severity (Slovic, 1987). Risk perceptions vary with personal characteristics, social structure, and cultural beliefs (Neuburger and Egger, 2021). In the health domain, risk perceptions have been found to have a profound role in shaping health behaviour and are central to most health-specific behavioural theories (Weinstein, 1993; Sutton, 1987); these include the *health belief* model (Rosenstock, 1974), the *protection motivation* theory (Rogers, 1975), and the *extended parallel process* model (Witte, 1992).

On the other hand, broader behavioural theories are commonly used to elucidate health-related behaviours (e.g., the theory of *planned behaviour* by Ajzen, 1985; and the theory of *reasoned action* by Fishbein and Ajzen, 1975). These theories posit that potential health-specific dangers motivate people faced with hazards to change their previous behaviour. This conclusion has been verified in multiple contexts, such as earthquakes (Ainuddin et al., 2014), fires (Hahm et al., 2016), and the flu (Freimuth et al., 2017).

In particular, Slovic (1987) proposed that public risk perceptions are formed from the process of acquiring both positive and negative information about risk elements. By considering two dimensions of different risk elements, his work has aided risk analysis and policy-making by.

(1) Providing a basic tool - a *risk perception map* – designed for understanding and anticipating the public perception of hazards. Based on how people score two factors of different risk elements, risk perceptions can be visually displayed on this map.
   a) Factor 1, labelled *control*, is defined at its high end by perceived lack of control, dread, catastrophic potential, fatal consequences, and the inequitable distribution of risks and benefits.
   b) Factor 2, labelled *knowledge*, is defined at its high end by hazards judged to be unobservable, unknown, new, and delayed in their manifestation of harm.
(2) Improving the communication of risk information among laypeople and decision-makers. The approach assumes that those who promote and regulate health and safety need to understand how people process different kinds of information and use it to respond to risk.

Based on Slovic's work, this study aims to capture travellers' heterogeneous attitudes towards different types of information and explore how these influence risk perceptions. Additionally, the risk perception of different risk elements is shown visually on the risk perception map. As far as the authors are aware, this is the first time this tool has been used in a Covid-19 transportation scenario.

2.2. Perceived risk and travel behaviour

The perceived risks in travel, whether in general or to a specific destination, are highly correlated with intentions to modify travel behaviour, such as avoiding certain destinations or altering the transport mode (Kong et al., 2022; Schroeder et al., 2013). Furthermore, when perceived risks are deemed likely or severe, self-protection becomes relevant, leading to actions such as trip cancellation or travel mode alteration (Schroeder et al., 2013). Therefore, perceived risks may influence not only the choice of travel destination but also the transport mode. Neuburger and Egger (2021) investigated the link between Covid-19 perception, perceived risk of travel, and travel behaviour among travellers in the DACH (Germany, Austria and Switzerland) region and found that the tourism market was severely impacted. However, their study did not consider risk perception as a latent variable, possibly resulting in endogeneity issues.

Some studies focus on exploring the relationship between the perceived risk of Covid-19 and daily travel behaviour (Zafri et al., 2022; Chen et al., 2022; Rahimi et al., 2021). For example, Chen et al. (2022) explored the influence of social responsibility, risk perception, attitudes of fear, and travel anxiety on travel behaviour. They found that the willingness to travel during the pandemic diminished, in general, and also that the travel time and cost attributes became less relevant when choosing public transport. However, these papers did not focus on how

[1] Xinhua net China Network: http://www.xinhuanet.com/politics/2021-01/16/c_1126989719.htm Accessed 16.01.2021.

risk perceptions are formed and how different risk communication strategies influence travellers' risk perceptions.

2.3. Information and risk communication

To enhance individuals' and institutions' awareness about risks and hazards, and to encourage health-protective behaviour, it is crucial to have an effective and precise exchange of information on health-related risks and hazards, particularly during emergencies (DiClemente et al., 2016). Effective risk communication strategies necessitate a comprehensive understanding of people's perceptions, concerns, knowledge, and practices. They are a vital component of risk reduction initiatives, as they foster public understanding, trust, acceptance, and adherence to the prescribed measures (World Health Organization, 2020). If people have accurate information about the risks faced and knowledge about their prevention, compliance with public safety advice by the government often increases (Barry, 2009).

Studies have proved that risk communications based on proper information can be efficacious in improving cognitive and behavioural outcomes (Qiu et al., 2020; Zhang et al., 2020). Risk perceptions can predict engagement in protective behaviour during pandemic events (Scherr et al., 2016), including crises such as Covid-19 (Wise et al., 2020). Furthermore, risk communication interventions can directly change behaviour, which is promising. Chatterjee et al. (2020) summarised risk communication strategies during Covid-19 around the world, including tools to provide information: Infermedica, Health Engine, Henryford, Humandx.org, etc. These strategies have proved effective to some extent. However, there are few studies focused on designing risk communication strategies based on travellers' travel risk perceptions.

2.4. Hypotheses

Based on the above discussion of the literature, we propose the following hypotheses related to the changes in travel behaviour with respect to risk perception due to Covid-19 and information about the pandemic.

Hypothesis 1. Perceived risks have a significant impact on the choice of mode and corresponding usage frequencies in the context of Covid-19.

Research has shown that the public's risk perceptions and attitudes are closely related to the position of a risk element within the factor space of the risk perception map. The primary factor of concern is the horizontal dimension of *perceived lack of control and dreaded risk* (Slovic, 1987). Hazards that rank higher on this factor (appearing further to the right on the map) are viewed as having a greater level of perceived risk. Consequently, individuals express a greater desire to reduce current risks and advocate for strict regulations to achieve the desired risk reduction. Meanwhile, unfamiliar elements have a similar impact. Therefore, the risk elements which are located in the first, second and fourth quadrants of the map lead to higher risk perception. Risk perception has impacted traveller behaviour in past epidemic scenarios and other hazard scenarios, such as Ebola (Cahyanto et al., 2016).

Hypothesis 2. The perceived risk is substantially influenced by the type of information provided. More specifically,

a. The attitudes towards positive information related to Covid-19 should reduce the perceived risk of using public transport;
b. The attitudes towards negative information related to Covid-19 should increase the perceived risk of using public transport;

Previous studies show that negative information about a hazard, such as the number of infection cases and the number of deaths, is more likely to increase the risk perceived by individuals, and even lead to irrational panic among the public (Kan et al., 2003); on the contrary, positive information, such as cure cases, government prevention measures and the development of vaccination can reduce the risk perception level of individuals (Abrams et al., 2020; Herovic et al., 2020). During the Covid-19 epidemic, travellers obtained various travel-related information through media, government propaganda etc.

3. Study design and methodology

3.1. Data collection and participants

Fig. 1 shows the Covid-19 timeline for Beijing in 2020–21. In the initial two waves, the government enforced mandatory lockdowns to contain the spread of infections, resulting in the closure of public facilities and business and stay-at-home orders. In contrast, during the third wave, the primary prevention strategies to combat Covid-19 involved advocating social distancing, mandating using face masks in public spaces, and other measures. Consequently, the influence of Covid-19 on travel mode use during this period is directly linked to the perceived risk of infection by travellers since travelling was illegal during Wave 1 but possible (with a choice) during Wave 3. For these reasons, we collected data for modelling the relationship between risk perceptions and travel behaviour during Wave 3.

To mitigate the risk of infections associated with in-person data collection, we employed a web-based survey administered through a professional survey panel - specifically, the oldest and largest online survey platform in China, https://www.wjx.cn/, which is known for collecting high-quality data from a representative sample (Wang et al., 2020). This platform ensured that the data collected was representative of the local population (Wang et al., 2020). Since the survey targeted Beijing residents with similar pandemic experience, screening questions were used to exclude respondents who did not reside in the city throughout all three waves of the pandemic, resulting in the recruitment of 512 Beijing residents who completed the questionnaire. Out of these, 424 (82.8% valid rate) passed the screening process, and their descriptive statistics are shown in Table 1. Note that because it is difficult to reach the elderly using online questionnaires, there are relatively few people over 60 in the sample. This may result in insufficient insights into the elderly population in this paper.

3.2. Information about risk elements

We asked participants to indicate their level of knowledge and capacity to control the risk-related elements shown in Table 2.

The design of risk elements considered three steps: (i) selecting candidate (i.e., widely discussed) elements from the news and social media; (ii) screening candidate elements through focus groups; only the most important were retained; (iii) conducting expert interviews to help us decide which elements were worth studying. Then, the pilot questionnaire was distributed to ordinary people in non-medical fields and collected their suggestions. Based on their feedback, the questionnaire was modified to ensure that the concepts and sentences used were easily understood by ordinary people. This process led to the retention of 17 risk elements divided into three categories (the full list of elements is given in Table 2). For each element, participants provided their level of *knowledge* on a 5-point Likert scale, going from "completely familiar" to "completely unfamiliar"; they also provided their level of *control* on a 5-point Likert scale going from "completely controllable" to "completely uncontrollable". The idea is that people's risk perceptions and attitudes are closely related with the position of a risk element within this type of factor space.

3.3. Identification of variables for modelling

The primary focus of our study was the frequency with which individuals chose various transport modes on a weekly basis, both before and during the Covid-19 pandemic, which was self-reported by the

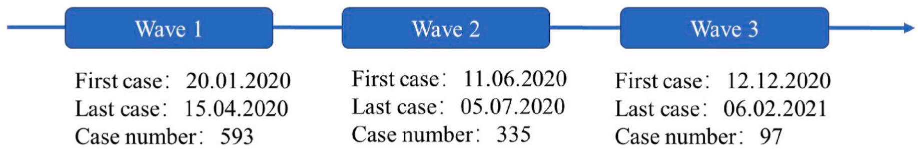

Fig. 1. Timeline of Covid-19 in Beijing.

Table 1
Descriptive statistics of the respondents.

Socio-demographic attributes		Sample (%)	Beijing Census (%)
Gender	Woman	53.07	48.9[a]
	Man	46.93	51.1
Age	18–24	9.43	68.5[a]
	25–29	27.36	
	30–39	44.81	
	40–49	13.68	
	50–59	3.30	
	60–69	0.94	19.6
	70 or more	0.47	
Personal annual income	Less than ￥30,000	4.72	42[b]
	￥30,000-￥80,000	11.32	
	￥80,000-￥120,000	28.77	
	￥120,000-￥200,000	38.21	58
	￥200,000-￥300,000	12.26	
	More than ￥300,000	4.72	
Education level	No formal education	0.47	–
	Junior high school and under	0.47	
	Senior high school	2.83	
	Vocational college degree	5.66	
	Bachelor's degree	70.75	
	Master's degree	18.87	
	Doctoral degree or above	0.94	
No. of cars in household	0	28.77	–
	1	64.15	50[c]
	2 or more	7.08	–

[a] http://www.beijing.gov.cn/gongkai/shuju/sjjd/202105/t20210519_2392877.html.
[b] https://m.gmw.cn/baijia/2020-12/30/1301987046.html.
[c] https://m.thepaper.cn/baijiahao_18953593.

participants. The alternatives included six modes: car, public transport (i.e., bus and subway), taxi (includes online ride-hailing), active modes (i.e., bike and walk), shared bike, and others (e.g., motorbike). We count data on seven trip frequency categories for using the six travel modes (1–6, ≥7 times per week). Therefore, the dependent variable has a multiple discrete-continuous nature with two components: (i) discrete mode choice and (ii) continuous mode-specific weekly trip frequency. Although trip frequency is an integer variable, the MCDEV model can still be used effectively for this kind of data (Shamshiripour et al., 2020; Calastri et al., 2017).

Fig. 2 shows that after the breakout of the infection, travellers tended to avoid using public transport and shifted to private travel modes. On the other hand, the average frequency change of the various modes is shown in Fig. 3. Within our sample, the use of public transport decreased the most, and the use of cars increased the most.

Fig. 4 shows the travel frequency proportion of the different modes. We merged walk and bike as active mode. The average proportion using public transport decreased from nearly 38% to about 23%. The proportion using private cars increased the most, from 12% to 19%.

We also asked participants about their longest travel distance before and during the pandemic. As shown in Fig. 5, during the pandemic, the long-distance (above 25 km) travel frequency decreased and the short-distance (below 10 km) travel frequency increased.

In addition, information was collected about socio-demographic

Table 2
List of risk elements.

Categories	risk elements
Risk elements concerning the virus	1) Virus 1-Infectivity of Covid-19 2) Virus 2-Cause of Covid −19 3) Virus 3-Virus variation[a] 4) Virus 4-Asymptomatic carrier[b] 5) Virus 5-Cure rate of a severe patient 6) Virus 6-Potential sequelae[c] 7) Virus 7-Long-term coexistence of the coronavirus and humans 8) Virus 8-Covid-19 vaccine risk 9) Virus 9-Development of Covid-19 specific remedy 10) Virus 10-Urban preventive measures 11) Virus 11-Fake news and fake preventive measures
Risk elements associated with using public transport during Covid-19	1) PT 1-Public transport staff and drivers' health 2) PT 2-Potential risk of passenger density in public transport vehicles 3) PT 3-Preventive measures on the public transport system
Risk elements associated with using taxis and online car-hailing during Covid-19	1) Taxi 1-Taxi and online car-hailing drivers' health status 2) Taxi 2-Taxi and online car-hailing passengers' health status 3) Taxi 3-Preventive measures of taxi and online car-hailing

[a] It refers to genetic mutations that occur during the spread of the virus, resulting in changes in the nature, contagious ability, and scope of infection of the virus (Tregoning et al., 2021).
[b] It refers to a virus carrier who is infected but is not displaying any signs or symptoms yet. However, the carrier has the potential to spread the virus to others (Zhao et al., 2020).
[c] It refers to the possible after effects or secondary consequences that may arise following infection with the Covid-19 virus, such as respiratory problems, cardiovascular issues and neurological symptoms (Troyer et al., 2020).

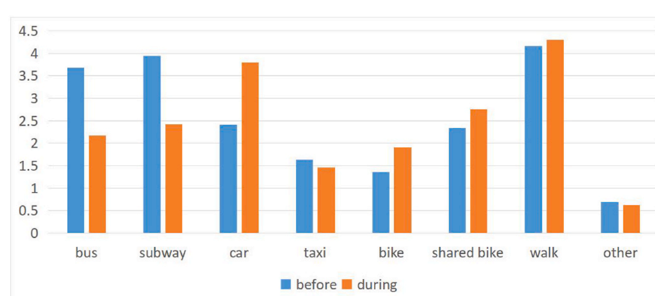

Fig. 2. Before/During comparison– average frequency of different travel modes in a week
Note: The X-axis represents travel modes. The Y-axis represents the average weekly trip frequency. The blue histogram represents the average frequency before the pandemic, and the orange during the pandemic. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

characteristics (e.g., age, gender, income, education), mobility

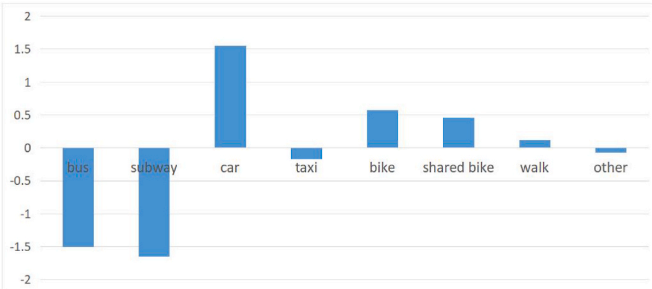

Fig. 3. Frequency change
Note: The X-axis represents travel modes. The Y-axis represents the gap in average weekly travel frequency during the pandemic compared with data before the pandemic.

behaviour (e.g., number of cars, bicycles available to you), health conditions (e.g., health status, vaccination status), home location (e.g., whether or not in the Covid-19 affected district) and the household (e.g., if there are vulnerable household members, if the other household members had objections regarding public transport use). These variables will be incorporated into the model as independent variables to analyse their impact on mode choice and on the specification of the latent variables.

3.4. Model structure

We formulated and estimated a hybrid choice model structure, incorporating a multiple discrete-continuous extreme value (MDCEV) model and a MIMIC model. The MDCEV model considers the selection of one or more options from a set of alternatives, followed by the selection of a non-negative quantity for each selected option (Bhat, 2005, 2008). On the other hand, the MIMIC model is a confirmatory factor analysis model that includes explanatory variables, which serve as causal indicators of the structural model (Motoaki and Daziano, 2015). The specification described in Fig. 6 shows the structure of the hybrid-choice model.

In the MIMIC model component, three potential latent concepts were considered (Slovic, 1987): (i) attitudes toward positive information; (ii) attitudes toward negative information, and (iii) perceived risk of using public transport. To measure these latent variables, respondents were required to indicate to what extent they were concerned about the indicators shown in Table 3 using a five-point Likert scale. Recall that the perceived risk of using PT was measured from two aspects *knowledge* (familiarity) and *control*, as was shown in Table 2.

The MIMIC model consists of two parts: the measurement model and the structural equations model. The former represents the link between the latent variable and its indicators and is specified by equation (1):

$$y_0^* = \widetilde{\delta} + \widetilde{d}z^* + \widetilde{\xi}, \widetilde{\xi} \sim N(0, \Theta) \quad (1)$$

where the vector y_0^* identifies the latent variable's indicators and $\widetilde{\delta}$ is a

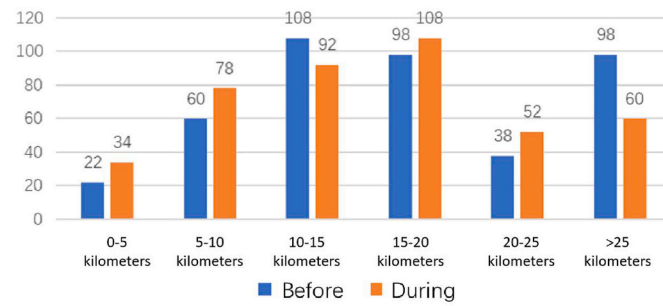

Fig. 5. Comparison of the longest distance travelled in a single trip within a week before/after the pandemic
Note: The X-axis represents the longest travel distance for trips in a week. The Y-axis represents the number of observations. The blue histogram represents the number before the pandemic, and the orange during the pandemic. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

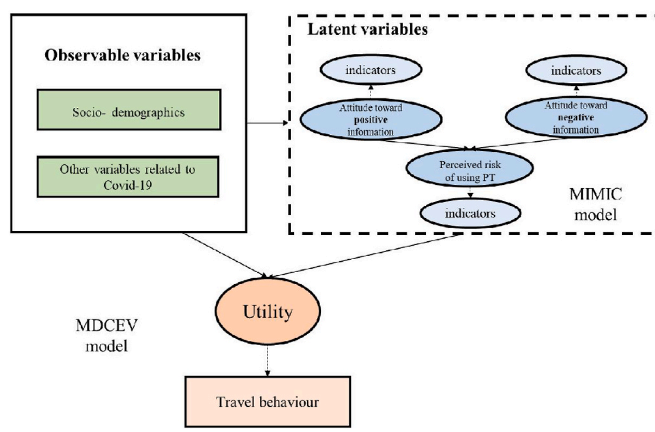

Fig. 6. Structure of the hybrid-choice model.

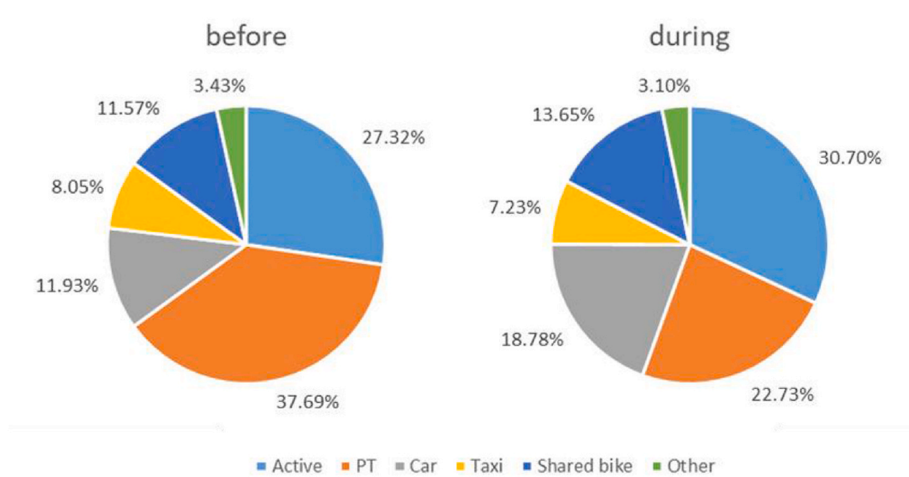

Fig. 4. Mode shares before and during the pandemic.

Table 3
Indicators for potential latent variables.

Latent variables	Indicators
Attitudes towards positive information	I_1: PT scheduling and passenger flow limitation measures I_2: PT disinfecting measures I_3: Protection measures for PT drivers and staff I_4: PT passenger trip tracking
Attitudes towards negative information	I_5: Report on PT driver's illness I_6: Report about infection cases in the PT system I_7: Report of possible contacts with Covid-19 infected people in the PT system
Perceived risk of using a public transport mode	I_8: Familiarity-PT staff and drivers' health I_9: Familiarity-potential risk of passenger density in PT vehicles I_{10}: Familiarity-preventive measures on the PT system I_{11}: Controllable-PT staff and drivers' health I_{12}: Controllable -potential risk of passenger density in PT vehicles I_{13}: Controllable -preventive measures on the PT system

vector of constant terms; the latent variable loading matrix is represented by $\widetilde{d}$, the latent variable itself by z^*, and $\widetilde{\xi}$ is a normally distributed error term with mean zero and a diagonal covariance matrix Θ.

The structural equation (2), represents the effect of the observable variables on the latent variables:

$$z^* = \omega\rho + \eta \tag{2}$$

where ω is a matrix of covariates to explain the relationships between the latent variable z^* and its causes; ρ is a vector of a possible manifest cause of the latent variable z^*, and η is a vector of error terms.

For the MDCEV model, Bhat (2008) defines that an individual allocates the consumption quantity t_k to each alternative as in equation (3):

$$U(t) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{3}$$

This equation represents the total utility $U(t)$ obtained from consuming K available alternatives, with t representing the vector of consumption quantities for each alternative (assumed to be non-negative). The satiation effect is controlled through the parameters γ_k and α_k by exponentiating the consumption quantity, where γ_k determines whether corner solutions (zero consumption) or interior solutions (all-alternatives consumption) are allowed and controls the degree of satiation by changing the consumption quantity. Values of γ_k closer to zero indicate a greater degree of satiation. In addition, through the increase of consumption in alternative k, α_k reduces the marginal utility.

The baseline marginal utility for alternative k is represented by equation (4) and is determined by the parameter ψ_k (Bhat, 2005):

$$\psi_k = exp(\beta_0 + \beta' z_k + \lambda z^* + \varepsilon_k) \tag{4}$$

where the vector β' contains coefficients that correspond to the attributes described by the set z_k, which characterizes both the individual and alternative k; the matrix λ is made up of coefficients that correspond to the latent variable, while ε_k represents the influence of alternative k on the baseline utility. These attributes are independently distributed across all available alternatives, are independent of z_k, and are assumed to follow an extreme value distribution.

To detect whether the parameter estimates pre/during Covid-19 are significantly different, β' is set as in equation (5):

$$\beta' = \beta_{before-Covid} + \beta_{Shift\ for\ During-Covid}\delta \tag{5}$$

$$\delta = \begin{cases} 1 & during\ the\ Covid-19 \\ 0 & before\ the\ Covid-19 \end{cases}$$

where $\beta_{before-Covid}$ is the coefficients associated with the set of attributes of the alternatives before Covid-19; $\beta_{Shift\ for\ During-Covid}$ is the difference of parameters caused by Covid-19; δ is a dummy variable, describing whether the attribute is being used to explain mode use before or during Covid-19. Thus, we can directly infer whether the coefficient is significantly different before/during the pandemic. The satiation parameters and alternative specific constants (ASC) were estimated in the same way to allow for direct comparisons.

According to Bhat (2008), it is difficult to distinguish between the two satiation effects in empirical studies. This can create significant issues with identifying and estimating both γ_k and α_k for each alternative, potentially causing problems with the estimation process. Thus, Bhat (2008) suggests setting one of these two parameters to a fixed value. In the γ-profile case, recommended by Meister et al. (2022), the value of γ_k is estimated for each alternative and the parameters α_k are set to 0 for all alternatives. Thus, equation (3) is rewritten as:

$$U(t) = \sum_{k=1}^{K} \gamma_k \psi_k\, ln\left(\frac{t_k}{\gamma_k} + 1 \right) \tag{6}$$

We assumed a weekly trip 'budget' of 42 (6 travel modes * 7 levels of frequency), and set 'Active modes' as the base alternative for model estimation (as it was available to all travellers). Additionally, our aim was to examine the change in mode choice behaviour from before the Covid period to the during-Covid phase. (where the cost of using different modes remained unchanged); no price variations among alternatives were considered (Vallejo-Borda et al., 2023). Based on the data characteristics, no outside good was considered in this travel context (Meister et al., 2022). The R package Apollo (Hess and Palma, 2019) was used to jointly estimate the parameters using Maximum Likelihood Estimation (MLE).

The explanatory variables used are shown in Table 4. Note that some are represented as dummies for model estimation. The reference for each dummy variable is also shown.

4. Results

4.1. Risk perception map

We used the average values for *knowledge* (2.94) and *control* (3.05) as the origins of the coordinate system to draw the risk perception map. As shown in the map (Fig. 7), the risk elements related to the virus (see Table 2 for the definitions), *Virus variation* (Virus-3 in Fig. 7), *Potential sequelae* (Virus-6) and Long-term coexistence of coronavirus with humans (Virus-7) are perceived as the most unfamiliar and uncontrollable by the participants. *Infectivity of Covid-19* (Virus-1), *Urban preventive measures* (Virus-10), and *Fake news and fake preventive measure*

Table 4
List of explanatory variables.

Socio-demographics	Description	Data format
Gender	Male (base: female)	Dummy
Age	Below 30; 30–50 (base: above 50)	Dummy
Personal income	Below 80k; 80–200K (base: above 200K)	Dummy
Education level	Low; median (base: high)	Dummy
Number of cars	1, 2, 3 or 3+	Numerical
Number of bikes	1, 2, 3	Numerical
Home location	Pandemic area (base: no pandemic area)	Dummy
Other variables related to COVID-19		
Family-vulnerable to infection	Yes (base: no)	Dummy
Family members object to using PT	Yes (base: no)	Dummy
Vaccination status	Yes (base: no)	Dummy
Health condition	Good/above good (base: not good)	Dummy

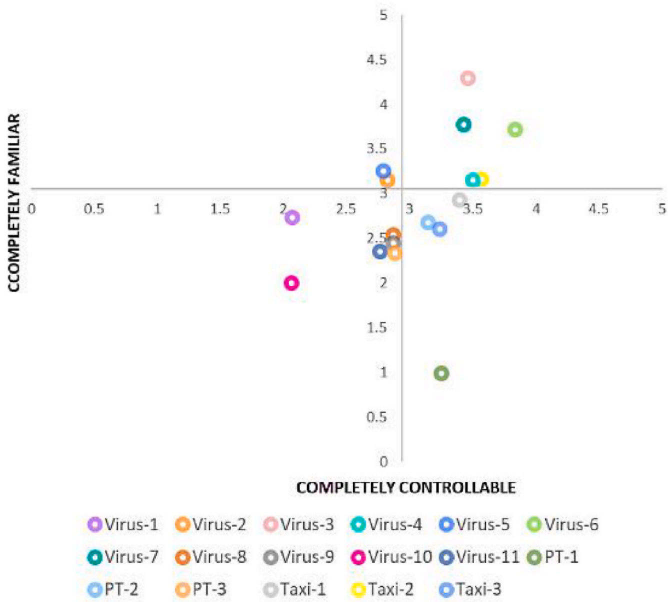

Fig. 7. Risk perception map.

(Virus-11) are in the third quadrant; this means that respondents know these three risk elements well and believe that they are controllable.

Most elements related to travel modes score lower than the average value in terms of *control* but higher than the average value in terms of *knowledge* (i.e., most elements are in the fourth quadrant). This suggests that current risk communication about these elements from the policy-makers to the public is inadequate and there is room for improvement.

4.2. Estimation results of the hybrid choice model

The MDCEV model estimation results are shown in Table 5a–c (only significant parameters are shown). Active modes were considered the reference alternative, so the alternative-specific constants (ASC) for the other modes signify the preference in comparison to the active modes when all other factors are held constant. The various independent variables (bold italic) have specific values for the different travel alternatives. The table also reports the satiation parameters γ_k.

The baseline utility refers to the marginal utility of a particular mode of travel when no consumption occurs. The ASC of PT are higher than the reference (Active modes) before Covid-19, but the ASC of all the other modes are lower. This suggests that other things being equal, travellers show a preference for PT over the other travel modes before Covid-19. However, this shifted during Covid-19 and all else being equal, PT was less preferred relative to the active modes, which is in line with the findings of previous studies (Liu et al., 2022; Meister et al., 2022; Zhao and Gao, 2022). On the contrary, all else being equal, the preferences for cars and shared bikes increased.

In terms of the influence of socio-demographic variables, the model suggests that there is a significant declining propensity for choosing PT among male respondents during Covid-19, while their use of cars and shared bikes increases. Younger respondents prefer PT and shared bikes both before and during Covid-19. Low-income individuals are more likely to choose PT, perhaps as a result of being unable to change mode. As would be expected, individuals who own more cars and those who live in areas with Covid-19 cases reduced their use of PT significantly. In addition, compared to travellers with higher education levels, travellers with medium level education appear to be less willing to use PT during Covid-19.

The model also yields intuitive results for other variables related to Covid-19. For example, if there are individuals in the family who are vulnerable to infection, such as the elderly and young children,

Table 5a
Estimation results for the Hybrid-MIMIC-MDCEV model.

Model parameters	Before Covid		Shift for During-Covid	
	Estimate	Robust t-stat	Estimate	Robust t-stat
ASC (β_0)				
Car	−1.26	−4.22	0.14	5.23
Public transport	2.86	3.48	−3.72	−6.36
Taxi	−2.45	−2.72	−0.22	−4.19
Shared bike	−1.30	−4.37	0.09	3.53
Other	−4.12	−2.19	−0.13	−2.88
Explanatory Variables (β')				
Male				
Car	0.25	4.24	0.18	2.33
Public transport	0.60	2.97	−1.61	−1.67
Shared bike	0.20	1.67	0.73	3.79
Age-under 30				
Public transport	0.15	1.99	0.04	2.00
Shared bike	0.60	6.15	0.18	7.76
Income_p(below 80K)				
Public transport	0.18	1.71	1.01	2.97
Income_personal(80-200K)				
Public transport	−0.31	−2.31	1.38	0.88
Education-median level				
Public transport	0.36	2.74	−0.50	−2.79
Number of cars				
Car	0.45	2.24	0.44	3.19
Public transport	−0.31	−4.36	−0.29	−2.65
Home loc.-Pandemic area				
Public transport	0.78	1.31	−1.01	−4.45
Shared bike	−0.17	−0.74	1.33	2.50
Family-vulnerable to infection				
Public transport	0.14	1.41	−0.66	−1.94
Family members object to using PT				
Public transport			−1.42	−3.04
Health status(above 'good')				
Shared bike			0.15	2.68
Vaccine				
Car			−0.03	−2.67
Public transport			0.16	3.43
Shared bike			0.29	4.07
LV- Perceived risk of using public transport (λ)				
Car			0.24	2.32
Public transport(bus subway)			−0.27	−5.37
Shared bike			0.35	2.17
Satiation parameters (γ)				
Active modes	2.01	3.68	0.09	2.36
Car	1.62	5.12	0.23	3.56
Public transport	2.48	3.21	−0.49	−4.33
Taxi	0.95	4.20	−0.04	−5.12
Shared bike	1.43	7.31	0.32	6.75
Other	0.53	2.42	−0.03	−2.98
Goodness of fit (whole model)				
Log-likelihood (null)			−6098.72	
Log-likelihood			−4842.69	
AIC			8873.35	
BIC			7521.47	

respondents prefer not to use PT during Covid-19; this also occurs if there are family members who object to the use of PT. Travellers with very good health prefer to use shared bikes during the pandemic. Further intuitive results include that if respondents had been vaccinated against Covid-19, the use of PT and shared bikes increased significantly, and the use of cars decreased. Finally, in terms of perceived risks, people with a higher perceived risk of PT are less likely to use PT but more likely to use shared bikes and cars during the pandemic.

The satiation parameters γ determine the satiation effect of the travel

Table 5b
MIMIC- Measurement model.

	Estimate	Robust t-stat
Attitudes towards positive information		
PT scheduling and passenger flow limitation measures	1 (fixed)	
PT disinfecting measures	1.84	3.47
Protection measures for PT drivers and staff	2.79	4.81
PT passenger trip tracking	1.37	3.74
Attitudes towards negative information		
Report on PT driver's illness.	1 (fixed)	
Report about infection cases in the PT system.	3.19	7.75
Report of possible contacts with Covid-19 infected people in the PT system.	4.61	6.63
Perceived risk		
Familiarity-PT staff and drivers' health	1 (fixed)	
Familiarity-potential risk of passenger density in PT vehicles	4.85	2.33
Familiarity-preventive measures in the PT system	4.21	4.56
Controllable-public transport staff and drivers' health	4.07	3.67
Controllable -potential risk of passenger density in PT vehicles	2.49	2.26
Controllable -preventive measures on the PT system	4.75	6.14

Table 5c
MIMIC- Structural model.

Latent variables (ω)	Estimate	Robust t-stat
Attitudes towards positive information		
Male	−0.30	−1.89
Age-30-50	0.07	2.86
Number of cars	−0.68	−3.18
Vaccine	−0.12	−1.79
Attitudes towards negative information		
Age-below 30	0.53	3.34
Income_p-Below 80k	0.72	2.57
Family-vulnerable to infection	0.25	3.69
Vaccine	−0.14	−3.97
Pandemic area	0.46	1.93
Perceived risk		
Male	0.70	2.82
Education-low	0.13	2.69
Education-median	0.08	3.34
Family-vulnerable to infection	0.53	5.26
Health status-good	0.11	2.76
Attitudes towards positive information	−0.38	−4.36
Attitudes towards negative information	0.53	1.75

frequencies for each mode. A lower satiation parameter suggests that travellers get satiated more easily with the use of that travel mode, and are less willing to use it. Before Covid-19, PT had the highest satiation parameter, followed by active modes, car, shared bike, taxi, and others. During Covid-19, the satiation parameters for all modes were ordered similarly, except for the case of PT and active modes. PT shows a strong decrease in its satiation parameter, while the satiation parameter values associated with cars and shared bikes increased the most.

The embedded MIMIC model's measurement equations decrease the dimensionality of the effect indicators, while the structural equations establish a causal relationship that clarifies how the latent variables are formeed (see Table 5b). The results show that both unfamiliarity and feeling uncontrollable significantly increase the perceived risk of using public transport. In conclusion, *Hypothesis 1* is supported.

Travellers show significant heterogeneity in the structural equations' component (Table 5c). The latent variable *attitudes towards positive information* was explained by gender, age, number of cars, and vaccination status. For example, travellers with a higher concern about positive information are those aged 30–50, women and individuals who have not yet been vaccinated. Meanwhile, the latent variable *attitudes towards negative information* was explained by age, income, number of cars, the health status of family members, if from a pandemic area, and vaccination. For example, if any people in the family was vulnerable to infection, the traveller would pay more attention to negative information. Further, when people get vaccinated, they would pay less attention to both types of information.

Finally, the latent variable *perceived risk* was affected by the other two latent variables. Finally, as the perceived risk of using PT is also influenced by gender, education level, and health status of the family members and travellers themselves, both *Hypothesis 2a* and *Hypothesis 2b* are supported.

5. Discussion and policy implications

The key findings of our research can be summarised as follows.

(i) The perceived risk has a significant impact on travellers' mode choices and their corresponding usage frequencies in the context of Covid-19. Travellers tend to reduce their use of public transport and increase their use of shared bikes (as shown by the estimate of λ in Table 5a).
(ii) The risk perception map drawn to visually explain which risk elements felt unfamiliar and uncontrollable to travellers (Fig. 7), shows that the risk elements located in the first, second and fourth quadrants lead to higher perceived risk (see section 4.1 for the details).
(iii) The perceived risk is influenced by the attitudes towards the positive and negative information, and travellers show significant heterogeneity in this sense (as shown in Table 5c).

These findings stress the importance of risk communication to shape risk perception. They also provide insights about the type of information that travellers would pay more attention to. Therefore, these insights can be effectively used to design targeted intervention strategies for different types of travellers. In addition, our results can be used to better predict the demand for other modes (e.g., shared bikes) and to design policies to change the supply side as appropriate. Our policy implications are discussed in detail below.

(1) Travellers' behaviour changes during Covid-19

Based on the results of Table 5a, this study shows the impact of the pandemic on travellers' mode choice and frequency. Similar to the results of previous studies (Liu et al., 2022; Meister et al., 2022; Zhao and Gao, 2022; Tirachini and Cats, 2020), the impact of the pandemic on public transport is obvious: travellers are reluctant to use subways and buses during the pandemic and are more inclined to use more personalised modes, especially private cars (as reflected in the mode-specific satiation parameters, γ).

Meanwhile, our data also suggests that shared bicycles were highly popular during the pandemic. Travellers were more willing to use this fast, open-environment, and personal way of travel, rather than taking the risk of sharing public transport space with other travellers. In addition, Fig. 5 shows that during the pandemic, travellers' demand for long-distance travel within the city decreased, while demand for short-distance travel increased. The characteristics of shared bicycles can well match the changing demand of travellers. The enlightenment we can get is that in the post-pandemic era, the government should not only focus on pandemic prevention measures for the public transport system but also make full use of the power of social travel service companies, such as shared bike companies. These provide more short-distance and safer alternative travel modes. More shared bikes can be placed in the community to meet the travel needs of residents and measures should be taken to ensure they remain safe to use in presence of infectious diseases.

Our study also finds a relationship between demographic variables and changes in travel patterns (as shown by the estimates of β' in Table 5a). These influences are significantly different among travellers.

First, males are more willing to use shared bikes. In terms of age, we find that young travellers, under 30, are more inclined to use shared bikes. This is not only because this mode is more in line with the identity of younger travellers, but also because younger travellers are more familiar with emerging technologies. Furthermore, the results show that compared with high-income groups, low and middle-income groups do not significantly reduce their public transport use. This is likely because they may have no budget to change their travel patterns. This stresses the importance of the need for governments to pay more attention to the travel behaviour of low and middle-income groups during the pandemic. These groups may need to use relatively higher-risk modes because they are, to some extent, captive.

(2) **Risk perception map and risk elements**

According to the risk perception map, *Virus variation*, *Potential sequelae* and *Long-term coexistence of coronavirus with humans* (i.e., those in the first quadrant of Fig. 7), are perceived as the most unfamiliar and uncontrollable threats by participants. In this regard, and referring to Slovic (1987), the government should convene relevant experts to better explain the above items to the public to reduce public risk perceptions.

At the same time, risk elements, such as *PT staff and drivers' health status*, and *Taxi and online car-hailing drivers' health status*, are located in the fourth quadrant of Fig. 7. In other words, most individuals in our sample think that these elements are controllable, but they are not familiar with relevant protection measures. Therefore, the government should strengthen its publicity about protection and control measures to reduce the perceived risk of travellers. For example, publicising the health status of drivers in the subway system, writing measures in the form of propaganda slogans and posting them in eye-catching places.

(3) **Risk communication**

Public risk perceptions are formed from the process of acquiring both positive and negative information (Slovic, 1987). This study explored how different types of information about Covid-19 may affect people's perceived risk. The results shown in Table 5c are in line with our hypotheses. More attention to positive information reduces the perceived risk, while negative information has the opposite effect. Positive information, such as government measures launched to control the pandemic, shown in Table 5b, enhance the public's sense of safety, thereby reducing the risk perception. Therefore, when people feel that the government's behaviour is reliable, their inner security will increase and their perception of risks decrease. While, negative information disclosure (such as the report of infection cases in the public transport system), makes travellers feel that their safety is compromised, the corresponding risk perception increases. When considering risk communication, the government should combine the use of positive information and negative information to help the public form an appropriately perceived risk, neither over-optimistic nor leading to over-panic.[2]

In addition, travellers show again significant heterogeneity, as shown in Table 5c. Therefore, when considering risk communication, the government should design targeted intervention strategies for different types of travellers. For example, middle-aged females are more concerned about positive information. Thus, the government should focus on advertising Covid-19 control measures to reduce their risk perceptions. In contrast, young, low-income groups are more concerned with the negative information about the pandemic. As they are the group with the lowest ability to avoid risks, once they contract the disease, their lives may be greatly affected. Thus, the government should be careful when providing information about the number of people infected with the pandemic, the hazards of the disease, etc., to avoid making them perceive higher risks. What's more, we find that after people vaccinate, their sensitivity to either type of information decreased. This shows that people may relax their vigilance after the vaccine and reduce their attention to the pandemic. However, there is evidence that if the virus mutates, the vaccine may fail.[3] Thus, the government should constantly update the latest situation concerning the pandemic in the case of people who have been vaccinated, to help them stay vigilant at all times.

Moreover, risk communication strategies, as a form of informational intervention, have the advantage of low cost and of subtly influencing people's behaviour. In a future pandemic, these softer measures can serve as a complement to harder restrictive policies, enhancing their acceptability for travellers and the effectiveness of behavioural interventions.

6. Conclusions

Our study contributes with a novel perspective about the factors influencing perceived risks and travel behaviour during a pandemic, and identifies different risk element profiles, as discussed above.

We conclude by acknowledging some of the limitations of our study and discussing potential directions for future work. Firstly, we only used data before and during the pandemic and did not consider the potential situation after the end of the pandemic. Subsequent research can consider whether travellers can return to their pre-pandemic conditions after the pandemic is over. Secondly, we used online questionnaire data, which may have some bias due to reporting errors. In particular, although this may be the most reasonable and safest way to collect data during a pandemic, it resulted in obtaining a smaller sample of people older than 60. Future research can try to use big data sources (i.e., subway smart cards, GPS data), which cover wider range of people, to capture the behaviour of the older population. Thirdly, considering the complexity and policy implications of our model, we emphasise the perceived risks related to public transport use. Consideration of more risk perception variables, such as those related to the virus characteristics in future research, could make the findings more detailed. In addition, this study focused on the impact of internal factors, and as such, many external factors were not incorporated in our model, such as work from home, restrictive policies, etc., which have been found to have impact on travellers' behaviour in other studies. In future work, it would be worth studying the interactive effects of external and internal factors. Notwithstanding, the findings of the paper regarding heterogeneity in risk perceptions and the potential effectiveness of the ways to change them can help policy makers to design targeted risk communication strategies without compromising the commitment to sustainable transport options.

Declarations of interest

The authors declare that they have no conflicts of interest in this work.

Author statement

Yu Wang: Conceptualization, Data Curation, Formal Analysis, Methodology, Original Draft, Review & Editing, Charisma Choudhury: Supervision, Conceptualization, Methodology, Review & Editing, Thomas O. Hancock: Supervision, Conceptualization, Methodology, Review & Editing, Yacan Wang: Supervision, Conceptualization, Funding, Review & Editing, Juan de Dios Ortúzar: Conceptualization, Review & Editing.

[2] China's government used "war-time" to describe the status of the pandemic, which caused some public panic.: http://static.scms.sztv.com.cn/ysz/zx/szws/78367224.shtml.

[3] https://news.sina.com.cn/o/2023-02-25/doc-imyhxqsi1437350.shtml.

Data availability

The authors do not have permission to share data.

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