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Investigating the Impact of the COVID-19 Pandemic on Travel Mode Choice Behaviour – A Stated Preference Case in Wuhan, China

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ABSTRACT

This paper investigates the impact of the COVID-19 pandemic on travel modes choice behaviour using a case study from Wuhan, China. A SP-experiment based survey was conducted in Wuhan, based on which an MNL model and a latent class MNL model were established, respectively. The model estimation results show the following conclusions. First, the attributes that are normally believed to significantly affect the residents' travel mode choice behaviour turned out to be insignificant during the COVID-19 pandemic. Second, attributes such as age, gender, driving license, income trend, use frequency of public transit, currently most-frequent-used mode, household size, monthly household income, distance from metro station to home, number of confirmed/deaths cases, vaccination are significantly affecting the respondents' travel preferences. Third, the outbreak of the COVID-19 pandemic leads to a decline in the residents' preferences toward public transit, but the promotion of vaccines can lead residents to return to the public transit system. Fourth, the respondents were divided into three latent classes: high-susceptible, medium-susceptible and low-susceptible classes. These conclusions are believed to provide a reference for the investigation of impact of the COVID-19 pandemic or other similar public health events on the transportation system, and also offer supports for policy-making to effectively deal with such pandemics.

KEYWORDS

travel mode choice; COVID-19 pandemic; MNL model; latent class; Wuhan city.

1. INTRODUCTION

Even though the COVID-19 pandemic has passed, its impact on a global scale has persisted. The WHO declared COVID-19 as a Public Health Emergency of International Concern (PHEIC) on 11 March 2020. Since 2009, the WHO has announced seven PHEIC declarations, namely, the ongoing 2022 monkeypox outbreak, the COVID-19 in 2019, the Kivu Ebola outbreak in 2018, the 2015–2016 Zika fever, the polio declaration in 2014, the 2013–2016 outbreak of Ebola in Western Africa and the H1N1 influenza virus in 2009 [1]. As one of the seven PHEIC declarations, the impact of COVID-19 on travel behaviour will be the focus of this study.

The first large-scale outbreak of COVID-19 occurred in Wuhan, China in December 2019. Wuhan was locked down for 76 days from 23 January to 18 April. During this period, the Provincial Epidemic Prevention and Control Centre in the Hubei province (Wuhan is the capital of the Hubei province) adjusted the regional risk level according to the actual situation of the epidemic. From 25 March to 17 April, Wuhan was adjusted to a medium-risk area, and from 18 April to a low-risk area [2]. Since 25 March, the public transportation system in Wuhan has partially resumed, and preventive measures have been taken according to the degree of epidemic risk. The government has issued the "Guidelines for the Divisional and Graded Prevention and Control of the New Coronary Pneumonia Epidemic in Passenger Terminals and Transportation Vehicles" [3] (hereinafter referred to as the "Guidelines"). The Guidelines require necessary measures of epidemic prevention and control for all transport modes according to various risk levels of the region. After fierce fights with the virus, taxis resumed operating on 8 April, and all public transportation in Wuhan resumed on 22 April. Finally, the online car-hailing resumed on 30 April. From the perspective of the results of epidemic prevention and control, Wuhan's epidemic prevention measures are undoubtedly successful, where rapid responses to the epidemic and strict epidemic prevention and control measures are the keys to the success of epidemic prevention.

During the COVID-19 period, some people changed their travel mode from public transportation to private cars. In China, more than 60% of trips were transferred from public transport to private cars [4]. Nan et al. [5] showed that in the period from 25 February to 31 March 2020 in China, there was a 39.2% increase in the proportion of population who chose car or taxi to finish the trips. This did not only happen in China. Research by Beck et al. [6] showed that residents in Australia still had concerns about using public transport to travel in July 2020. The residents' preferred travel mode tended to shift from public transport to private cars or taxis. Meanwhile, Basu and Ferreira [7] showed that 18% of car-free households planned to buy a car because of the COVID-19, and 26% of them planned to buy a car in the following year, which will increase people's preferences toward private cars.

However, existing research on the factors influencing travel behaviour during the COVID-19 pandemic remains insufficient. In particular, the impacts of confirmed COVID-19 cases on travel behaviour have not been sufficiently explored. A clear research gap exists regarding the impact of the number of vaccinated people on travel behaviour. Based on the above considerations, analysis toward people's travel behaviour in Wuhan is of great interest, especially because Wuhan is the first city that suffered from the COVID-19 pandemic and people's daily travel behaviour in Wuhan may be influenced the most when compared to other cities in China. In this sense, such analysis can provide unique insights and understandings about the influence of the COVID-19 pandemic on travel behaviour. Therefore, this study aims to investigate the impact of the COVID-19 pandemic on travel mode choice behaviour through a stated preference case in Wuhan. The main contribution of this study is that it provides insights about how people's mode choice behaviour and their corresponding preferences change after experiencing the hit of the COVID-19 pandemic.

The remainder of the paper is structured as follows. Section 2 describes the details of the questionnaire design and descriptive statistics of the collected data. Section 3 shows the specifications of the MNL model and the latent class MNL model. Section 4 gives the estimation results and some conclusions based on the results. Section 5 discusses and summarises the paper.

2. SURVEY AND DATA

In order to analyse the influence of the COVID-19 pandemic on the travel mode choice behaviour, an offline survey was conducted among residents living in Wuhan three months after easing lockdown. In that period of time, the local government of Wuhan had not imposed travel restrictions, but sporadic confirmed cases had emerged in other cities of China. In the first part of the questionnaire, respondents were presented a set of stated travel mode choice tasks in the context of different stages of the COVID-19 pandemic, while in the second part, the respondents were required to answer questions about their personal characteristics and travel mode preferences before and during the pandemic. In the last part, a set of household-related questions were presented.

2.1 Questionnaire design

In the first part of the questionnaire, a set of stated travel mode choice tasks were presented, where respondents were required to indicate which one of the four travel modes (i.e. car, bus, metro and taxi) was preferred. The details of these stated choice tasks are described as follows.

First, the travel-related and pandemic-related context attributes were taken into account. In order to examine the residents' general travel intentions in the context of the COVID-19 pandemic, we did not specify the travel purpose, but only hypothesised that the respondents "have something to do". "Have something to do" means non-recreational travel. Correspondingly, the travel destination of the trip was not specified but reflected by travel distance, which was also a context attribute in this study.

Attributes related to the COVID-19 pandemic, such as the numbers of daily or currently confirmed cases and the numbers of daily or total deaths, were also taken into consideration. To capture people's perception of the COVID-19 pandemic in more detail, we specified these attributes across cities in China (i.e. Wuhan vs. other cities in China). By doing so, we aim to capture the impact of outbreaks that occurred in different cities on people's preferences. Levels of these attributes were hypothetical and designed based on the cases during first outbreak period of the COVID-19 in Wuhan (from January to March 2020). In addition, the transmission rate R value was considered as it indicates the number of people who are infected by a single person, which represents the transmission capacity of the virus [8].

In this study, we examine urban travel mode choices under the influence of government-suggested policies and hypothetical vaccination scenarios during the COVID-19 pandemic. We consider both context attributes (e.g. government recommendations on gatherings, vaccination status) and alternative-specific attributes (e.g. travel time, crowdedness, fares, waiting time, departure frequency). Special attention is given to public transit attributes, including lower fares to attract riders, crowdedness concerns and the dual impact of departure frequency on infection risk. These factors are examined to understand their influence on the residents' travel mode choices in the pandemic context.

Note that the levels of travel time for all travel modes, travel cost for taxi, original ticket fare for metro (the final ticket fare presented to respondents were multiplied by the discount) are all related to travel distance. Therefore, in this study, they are calculated and translated according to the corresponding travel distance. For private cars, we assume that residents do not have to pay any cost for a single trip.

Table 1 – Attributes and corresponding levels

<table>
<tr><th colspan="2">SP attributes</th><th>Corresponding levels</th><th colspan="2">SP attributes</th><th>Corresponding levels</th></tr>
<tr><td colspan="3">Attributes related to COVID-19 pandemic</td><td colspan="3">Alternative-specific attributes</td></tr>
<tr><td rowspan="3">Wuhan</td><td>Currently confirmed cases</td><td>0, 50, 500, 5000</td><td colspan="2">Bus ticket fare (CNY)</td><td>0, 0.5, 1.0, 1.5</td></tr>
<tr><td>Daily confirmed cases</td><td>0, 10, 100, 1000</td><td colspan="2">Metro ticket discount</td><td>0%, 33%, 66%, 100%</td></tr>
<tr><td>Daily deaths</td><td>0, 10, 100, 1000</td><td colspan="2">Departure frequency of bus</td><td>Increased, decreased</td></tr>
<tr><td rowspan="3">Other cities</td><td>Currently confirmed cases</td><td>0, 50, 500, 5000</td><td colspan="2">Departure frequency of metro</td><td>Increased, decreased</td></tr>
<tr><td>Daily confirmed cases</td><td>0, 10, 100, 1000</td><td rowspan="3">Waiting time (min)</td><td>Bus</td><td>3, 13, 21, 29</td></tr>
<tr><td>Daily deaths</td><td>0, 10, 100, 1000</td><td>Metro</td><td>3, 6</td></tr>
<tr><td colspan="2">Vaccinated or not</td><td>Yes, No</td><td>Taxi</td><td>5, 10, 15 ,20</td></tr>
<tr><td colspan="2" rowspan="2">Government recommends to reduce gathering</td><td rowspan="2">Yes, No</td><td rowspan="4">Travel time (min)</td><td>Metro</td><td>16, 32, 35, 48</td></tr>
<tr><td>Bus</td><td>22, 38, 50, 57</td></tr>
<tr><td colspan="3">Context attributes</td><td>Taxi</td><td>17, 20, 24, 28</td></tr>
<tr><td colspan="2">Travel distance (KM)</td><td>5, 10, 15, 20</td><td>Car</td><td>12, 20, 24, 28</td></tr>
<tr><td colspan="6">Insignificant attributes from pilot survey</td></tr>
<tr><td colspan="2">Vaccination status of relatives and friends of respondents</td><td>None, Few, Most, All</td><td colspan="2">Crowdedness in bus</td><td>Crowded, Uncrowded</td></tr>
<tr><td colspan="2">R-value of COVID-19</td><td>1~3, 4~6, 7~9, 10~12</td><td colspan="2">Crowdedness in metro</td><td>Crowded, Uncrowded</td></tr>
</table>

The attributes and the corresponding levels considered in this study are presented in *Table 1*. Furthermore, an orthogonal design was adopted for experiment design using the R package *support.CEs* [9]. In pilot, we had 20 attributes where 13 attributes had 4 levels, and 7 attributes had 2 levels. 48 profiles were generated through the orthogonal design and divided into 6 blocks with 8 profiles in each block. The MNL model was used to identify the significant of attributes in pilot. We deleted five insignificant attributes in the pilot. Consequently, there were 15 attributes in the formal survey of which 10 attributes had four levels and five attributes had two levels. In formal survey, there were still 48 profiles which were divided into six blocks with eight profiles in each block.

Finally, the respondents' personal and household information was collected after the stated choice tasks. Specifically, information such as the respondents' age, gender, individual income, household income, household size and car ownership were collected. In addition to the personal-related attributes of the respondents, the related attributes of the COVID-19 pandemic were considered, such as whether they had been infected with the new coronavirus. More details about the information we collected can be found in *Table 2*.

2.2 Data collection

The study employed an offline survey methodology, facilitated by the Sojump platform (*https://www.wjx.cn/vj/tegaL3K.aspx*). Data collection occurred from 14 July to 1 August 2021, at various urban locations in Wuhan, including public transit hubs and shopping centres. To ensure data quality, respondents received a 20-Yuan incentive upon completion.

The research process comprised two phases: a pilot survey (14–17 July) and a formal survey (24 July–1August). The pilot conducted across multiple districts yielded 120 valid responses out of 131 collected, serving to refine the questionnaire. The subsequent formal survey, focused within Wuhan's Third Ring Road, resulted in 371 valid responses from 390 collected.

Strict validity criteria were applied, excluding responses completed too quickly, those from minors or full-time students, and car-choice inconsistencies. *Table 2* provides detailed sample characteristics.

Table 2 – Descriptive statistics of respondents' personal-related characteristics

Personal-related characteristics					
	Level	**Sample size**		**Level**	**Sample size**
Gender	Male	54%	Distance from home to the nearest metro station	≤500m	33%
	Female	46%		(500m, 1,000m]	34%
Age	18~24	26%		(1,000m, 1,500m]	17%
	24~30	30%		(1,500m, 2,000m]	4%
	31~40	32%		＞2000m	12%
	41~50	10%	Frequency of use public transport (before COVID-19)	Almost never	21%
	51~60	2%		Seldom	35%
Have driving license or not	Yes	77%		Often	32%
	No	23%		Almost everyday	12%
Income trend (2019~2020）	Increase	27%	Currently the most frequently used means of transportation	Bus	8%
	Steady	56%		Metro	49%
	Decrease	10%		Bike/Shared bike	5%
	Wave	7%		Taxi/ Car-hailing	5%
				Car	27%
				Electric bicycle	5%
Household-related characteristics					
Household size	1~2	11%	Household monthly pre-tax income (CNY)	Under 10 thousand	25%
	3~4	73%		10–20 thousand	41%
	5~6	13%		20–30 thousand	17%
	7 above	3%		Above 30 thousand	17%
Children need to be taken care of	Yes	27%			
	No	73%			

2.3 Pilot survey

Since the works on the influence of the COVID-19 pandemic on travel choice behaviour in the community are still in progress, it is difficult to determine which specific attributes had an impact on travel behaviour during the COVID-19 pandemic. Therefore, this study uses the data from the pilot survey to screen the considered attributes through a multinomial logit (MNL) model.

Analysis of *Table 1* highlights several factors that unexpectedly did not significantly influence the travel mode choice during the pandemic. These include public transit departure frequency, government recommendations on social gatherings, the coronavirus R value and vaccination status of one's social circle. The lack of impact from the R value may be due to its technical nature, potentially challenging for respondents to interpret. As a result of these findings, these non-significant factors were excluded from the subsequent formal survey design to focus on more influential variables in the pandemic-era travel behaviour.

3. MODEL SPECIFICATIONS

3.1 MNL model

Although the MNL model has certain limitations, its wide applications in practice make it one of the most classic discrete choice models [10]. Therefore, this study uses the MNL model as a starter. The following presents the utility functions of travel modes of a single respondent based on the designed questionnaire:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

$$V_{in} = \boldsymbol{\beta}_i^{\mathbf{0}} + \boldsymbol{\beta}_i^P \boldsymbol{X}_{in}^P + \boldsymbol{\beta}_i^E \boldsymbol{X}_{in}^E + \boldsymbol{\beta}_i^A \boldsymbol{X}_{in}^A \tag{2}$$

where U_{in} represents the utility of alternative i for individual n; V_{in} is the observed part of the utility U_{in}. ε_{in} is a random error term that follows the IID Gumbel distribution; $\boldsymbol{\beta}_i^{\mathbf{0}}$ is an alternative-specific constant; $\boldsymbol{X}_{in}^P$ is a P×1 vector of context attributes, which are related to the COVID-19 pandemic, such as confirmed cases, vaccination status, etc.; $\boldsymbol{X}_{in}^E$ is a E×1 vector related to the personal-related attributes of the respondents, including age, gender, monthly income before tax, household size, monthly household income before tax, etc.; $\boldsymbol{X}_{in}^A$ is a A×1 vector of alternative-specific attributes, including travel cost, travel time, waiting time/transfer time, crowding degree, etc.; P, E, A are the number of COVID-19-related attributes, personal-related attributes and alternative-specific attributes, respectively; $\boldsymbol{\beta}_i^P$ 、 $\boldsymbol{\beta}_i^E$ and $\boldsymbol{\beta}_i^A$ are the to-be estimated parameters of the COVID-19-related attributes, personal-related attributes and alternative-specific attributes, respectively; ε_{in} represents a random disturbance term for alternative i, which is the IID Gumbel distributed for MNL model. Maximum likelihood estimation for this model is similar to the Latent Class MNL and will be explained in the next section.

3.2 Latent class MNL model

Latent class model and random parameter model are often used to capture the heterogeneity of the decision makers' preferences. Random parameter model assumes that the taste parameters in the utility function follow a specific distribution. However, determining the specific distributions of taste parameters requires a large number of tests in practice, which takes a lot of time, especially when there are many random parameters. On the other hand, the latent class model does not have this issue, whose basic assumption is that there are a certain number of latent classes among respondents, and respondents in these latent classes show various preferences. In this sense, the latent class model is more applicable when there are many random parameters. In fact, evidence that latent class model outperforms the random parameter model can be found in the literature [11]. Panel effect is also considered in the latent class MNL when stated choice data are used. Based on these considerations, this study adopted a latent class MNL model to capture the heterogeneous preferences toward travel modes under the COVID-19 pandemic. The structure of the latent class MNL model includes two segments: membership function and utility function. The membership function is used to capture the probability that a respondent belongs to a certain latent class, and the utility function is used to capture the probability that a respondent will choose a certain alternative.

In the current study, the personal-related attributes of the respondents are used to identify the latent classes, and the logit form is adopted to indicate the membership probability of a respondent belonging to a latent class W_{ns}, which is given as follows:

$$W_{ns} = \frac{exp(\boldsymbol{\theta}_{i|s}^{E} \boldsymbol{X}_{in}^{E} + \theta_{0s}^{E})}{\sum_{s'=1}^{S} exp(\boldsymbol{\theta}_{i|s'}^{E} \boldsymbol{X}_{in}^{E} + \theta_{0s'}^{E})} \tag{3}$$

where $\boldsymbol{\theta}_{i|s}^{E}$ is a parameter-vector for attribute class and θ_{0s}^{E} is the constant to be estimated.

Suppose that the utility $U_{nit|s}$ of alternative i for respondent n in class s under choice situation t is as follows:

$$U_{int|s} = V_{int|s} + \varepsilon_{int|s} \tag{4}$$

$$V_{int|s} = \beta_{it|s}^{0} + \boldsymbol{\beta}_{it|s}^{P} \boldsymbol{X}_{int}^{P} + \boldsymbol{\beta}_{it|s}^{A} \boldsymbol{X}_{int}^{A} \tag{5}$$

where $V_{int|s}$ is observed part of the utility $U_{int|s}$; $\beta_{i|s}^{0}$ is an alternative-specific constant in class s under choice situation t; $\boldsymbol{X}_{int}^{P}$, $\boldsymbol{X}_{int}^{A}$ are the vectors of epidemic-related attributes and alternative-specific attribute, respectively; $\boldsymbol{\beta}_{it|s}^{P}$ and $\boldsymbol{\beta}_{it|s}^{A}$ are the to-be estimated parameters for class s; $\varepsilon_{int|s}$ is a random disturbance term for alternative i. The conditional probability $P_{int|s}$ of the respondent n in the class s choosing the alternative i under choice situation t can therefore be defined as follows:

$$P_{int|s} = \frac{d_{in} \cdot exp(V_{int|s})}{\sum_{j=1}^{J} d_{jn} \cdot exp(V_{jnt|s})} \tag{6}$$

Multiplying *Equations 6 and 10*, the probability for respondent n choosing alternative i can be obtained as follows:

$$P_{in} = \sum_{s=1}^{S} \prod_{t=1}^{T} P_{int|s} \cdot W_{ns} \tag{7}$$

In terms of model estimation, the maximum likelihood estimation technique can be adopted again. The log-likelihood function is shown in *Equation 12*.

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} y_{in} \cdot P_{in} \tag{8}$$

Before going to the estimation of the latent class MNL model, the number of latent classes needs to be determined first. In the literature, Bayesian Information Criterion (BIC) is often used as the index [12]. The commonly used method is to estimate latent class MNL models with different numbers of latent classes, and calculate their corresponding BIC values. The model with smallest BIC gives the number of latent classes that are finally used. The equation of the BIC is given as follows:

$$BIC = -2LL + Kln(M) \tag{9}$$

where LL is the log-likelihood value of the model at the convergence point, K is the number of parameters estimated in the model and M is the number of observations.

4. RESULTS

4.1 MNL model results

The MNL model described in Section 4.1 was estimated based on the collected data with the R package *mlogit* [13]. For the sake of model identification, the alternative car was set as the reference, which means the corresponding alternative-specific constant and taste parameters for context attributes were fixed as 0. Meanwhile, insignificant attributes were removed. Finally, 16 significant attributes remained, of which 4 attributes are related to the COVID-19 pandemic, 7 are related to personal attributes, 4 are related to household attributes and 1 is related to the travel mode-specific attribute. The ρ^2 of the model equals 0.2420, which indicates that the model has a satisfactory goodness of fit. In terms of attribute processing, case-related attributes (number of currently confirmed cases in Wuhan, number of daily deaths in Wuhan, etc.), travel cost, travel distance and waiting time are continuous, and other attributes are categorical therefore effects-coded [14] .

Before going into the details of the results of the MNL model, another thing should be addressed first. Previous studies [15] on travel mode choice behaviour usually use nested logit (NL) models to measure the potential correlations between the metro and the bus, or car and taxi. Based on this consideration, this study also established a NL model in addition to the MNL model. However, the results from the NL model confirm that the correlation between the metro and the bus, and car and taxi are not significant. From this finding, we can conclude that under the influence of the COVID-19 pandemic, people pay more attention to the relevant factors of the COVID-19 pandemic, but care less about the travel modes themselves.

Table 3 – Estimation results of the MNL model

	Metro		**Bus**		**Taxi**		**Car**	
	Est. (SE)	**p-value**	**Est. (SE)**	**p-value**	**Est. (SE)**	**p-value**	**Est. (SE)**	**p-value**
Pandemic-related attributes								
Wuhan daily confirmed cases	-0.0258 (0.0126)	0.0397 ***	-0.0382 (0.0198)	0.0539 **	-0.0056 (0.0145)	0.6981	0.0000	---
Other cities currently confirmed cases	-0.0068 (0.0026)	0.0080 ***	0.0003 (0.0038)	0.9312	0.0003 (0.0029)	0.9079	0.0000	---
Other cities daily deaths	-0.0401 (0.0128)	0.0017 ***	-0.0076 (0.0189)	0.6862	0.0026 (0.0144)	0.8561	0.0000	---
Vaccinated (reference)	-0.2052 (0.0525)	0.0001 ***	-0.1399 (0.0801)	0.0809 *	0.0251 (0.0619)	0.6847	0.0000	---
Not vaccinated	0.2052	---	0.1399	---	-0.0251	---	0.0000	---
Gender								
Male (reference)	0.2124	---	0	---	-0.0272	---	0.0000	---
Female	-0.2124 (0.0575)	0.0002 ***	0.0000 (0.0892)	0.9998	0.0272 (0.0668)	0.6839	0.0000	---
Age								
18~24 (reference)	0.4389	---	0.8816	---	0.9539	---	0.0000	---
25~30	0.7541 (0.1377)	0.0000 ***	0.5142 (0.1871)	0.0060 ***	0.7809 (0.1638)	0.0000 ***	0.0000	---
31~40	0.4383 (0.1488)	0.0032 ***	0.3978 (0.2111)	0.0595 *	0.1368 (0.1823)	0.4532	0.0000	---
51~60	-1.3859 (0.4076)	0.0007 ***	-1.5412 (0.4709)	0.0011 ***	-0.9905 (0.4595)	0.0311 **	0.0000	---
Income trend								
Increased (reference)	-0.4008	---	-0.2294	---	-0.2854	---	0.0000	---
Stable	-0.3714 (0.0905)	0.0000 ***	0.0220 (0.1459)	0.88	0.0830 (0.1116)	0.457	0.0000	---
Decreased	0.7429 (0.1502)	0.0000 ***	0.7674 (0.2327)	0.0010 ***	0.8445 (0.1887)	0.0000 ***	0.0000	---
Waved	0.0292 (0.1628)	0.8576	-0.5600 (0.2914)	0.0546 *	-0.6421 (0.2202)	0.0035 ***	0.0000	---
Driver's license								
Yes (reference)	-0.4643	---	-0.5479	---	-0.2265	---	0.0000	---
No	0.4643 (0.0757)	0.0000 ***	0.5479 (0.1019)	0.0000 ***	0.2265 (0.0863)	0.0087 ***	0.0000	---

Frequency of travel mode								
Never (reference)	-0.4657	---	-0.4657	---	-0.375	---	0.0000	---
Seldom	-0.2242 (0.0941)	0.0172 **	-0.2242 (0.0941)	0.0172 **	-0.5887 (0.1176)	0.0000 ***	0.0000	---
Often	0.2875 (0.1502)	0.0019 ***	0.2875 (0.0924)	0.0019 ***	0.2385 (0.1092)	0.0290 **	0.0000	---
Every day	0.4024 (0.1372)	0.0034 ***	0.4024 (0.1372)	0.0034 ***	0.7251 (0.1550)	0.0000 ***	0.0000	---
Most frequently used mode currently								
Bus (reference)	0.3836	---	1.6693	---	0.2786	---	0.0000	---
Car	-0.7484 (0.1248)	0.0000 ***	-0.9260 (0.2046)	0.0000 ***	-1.0518 (0.1585)	0.0000 ***	0.0000	---
Metro	0.2922 (0.1121)	0.0091 ***	-0.4129 (0.1597)	0.0098 ***	-0.1793 (0.1265)	0.1565	0.0000	---
Taxi	0.0727 (0.2091)	0.7282	-0.3305 (0.3163)	0.2961	0.9525 (0.2028)	0.0000 ***	0.0000	---
Distance between resident location and nearest metro station (only for metro)								
≤500m (reference)	0.225	---						
(500m, 1,000m]	0.2051	0.0065 ***						
(1,000m, 1,500m]	-0.2369	0.0180 ***						
＞1,500m	-0.1933	0.0541 **						
Household size								
1~2 (reference)	-0.3744	---	0.1516	---	-0.4256	---	0.0000	---
3~4	0.5626 (0.1202)	0.0000 ***	0.7450 (0.1882)	0.0001 ***	0.4880 (0.1374)	0.0004 ***	0.0000	---
5~6	0.5487 (0.1550)	0.0004 ***	0.1798 (0.2509)	0.4736	0.4102 (0.1852)	0.0267 **	0.0000	---
≥7	-0.7369 (0.2771)	0.0078 ***	-1.0764 (0.4407)	0.0146 **	-0.4726 (0.3147)	0.1331	-0.7369 (0.2771)	0.0078 ***
Monthly household income								
≤¥10,000 (reference)	0.023	---	-0.1571	---	0.0994	---	0.0000	---
(¥10,000,¥20,000]	0.3408 (0.0844)	0.0001 ***	0.3291 (0.1350)	0.0148 **	0.1689 (0.0998)	0.0905 *	0.0000	---
(¥20,000,¥30,000]	0.2796 (0.1050)	0.0077 ***	0.5669 (0.1740)	0.0011 ***	0.0678 (0.1346)	0.6145	0.0000	---
>¥30,000	-0.6434 (0.1179)	0.0000 ***	-0.7389 (0.2185)	0.0007 ***	-0.3361 (0.1330)	0.0115 **	0.0000	---
Children need to be taken care of								
Yes (reference)	-0.2069	---	-0.2442	---	0.0514	---	0.0000	---
No	0.2069 (0.0745)	0.0055 ***	0.2442 (0.1225)	0.0462 **	-0.0514 (0.0906)	0.57	0.0000	---
Crowdedness in metro and bus (metro & bus)								
Crowded (reference)	0.1121 (0.0446)	0.0120 ***	0.1279 (0.0731)	0.0802 *			0.0000	---
Uncrowded	-0.1121	---	-0.1279	---			0.0000	---

**** p-value<0.01; ** p-value<0.05; * p-value<0.1.*

Pandemic-related attributes

Table 3 shows the estimates of the taste parameters regarding the attributes related to the COVID-19 pandemic. Comparing to the car, the increase of daily confirmed cases in Wuhan can significantly reduce the respondents' preferences toward the metro (-0.0258) and the bus (-0.0382). In addition, currently confirmed cases in other cities (-0.0068) and daily deaths in other cities (-0.0401) would also reduce people's preferences for taking the metro. This means that people will consider the impact of the COVID-19 pandemic to a certain extent when making travel mode choices, and the increase of confirmed cases and deaths makes people leave the public transit system, which is in line with previous studies [16]. Meanwhile, we can also conclude from *Table 3* that the daily confirmed deaths in other cities have the greatest negative impact on people choosing the metro.

In terms of the attribute vaccination, the taste parameter of public transit for unvaccinated respondents is negative, indicating that unvaccinated respondents have lower preference toward public transit, and the sensitivity to metro of those respondents (-0.2052) is greater than that to bus (-0.1399). In other words, if a respondent is vaccinated against the new coronavirus, the possibility of them choosing public transit to travel would increase, especially the possibility of choosing the metro.

Personal-related attributes

Gender estimates in *Table 3* show that females are less likely to use the metro (-0.2124) compared to cars (0.000) during the COVID-19 pandemic, possibly due to higher risk sensitivity. Age estimates reveal a preference for cars among older respondents, with individuals over 40 demonstrating a particularly strong inclination towards private car use. Younger respondents (18–30) favour taxis over public transit. This shift may be attributed to declining immunity with age and increased car ownership due to wealth accumulation. Previous studies support this change in preference from public transit to private cars among older people during the pandemic [17]. Personal income trends during COVID-19 affect mode preferences. Those with increased income prefer cars over other modes, while those with decreased income favour taxis (0.8445) and buses (0.7674) over cars (0.000). Stable income reduces preference for metro (-0.3714), while fluctuating income decreases preference for buses (-0.5600) and taxis (-0.6421). Driver's license holders prefer cars (0.0000) the most, followed by taxis (-0.2265), the metro (-0.4643) and buses (-0.5479). This suggests their preferences are less likely to shift during the pandemic. Public transit usage frequency significantly impacts mode choice. Frequent users are more likely to choose public transit, with daily users showing the highest preference for taxis. Beyond public transit usage frequency, current mode preferences significantly influence choices. Users tend to stick with familiar modes, most notably for buses (1.6693), followed by taxis (0.9525), the metro (0.2922) and cars (0.0000). This consistency likely stems from pandemic-related uncertainties.

Household-related attributes

Household size impacts mode preferences. Smaller households (1–2 members) favour buses (0.1516) and cars (0.0000) over the metro (-0.3744) and taxis (-0.4256). Larger households (7+ members) prefer cars (0.0000) and prefer buses the least (-1.0760), possibly due to health concerns for family members. Monthly household income affects choices. Lower-income households (<10,000 Yuan) prefer taxis (0.0994) over buses (-0.1571). Middle-income groups (10,000-30,000 Yuan) favour public transit. Higher-income households (>30,000 Yuan) prefer cars (0.0000) and taxis (-0.3361) over buses (-0.7389) and the metro (-0.6434), likely prioritising health over cost. Having children requiring care reduces preferences for the metro (-0.2069) and buses (-0.2442), presumably due to concerns about children's weaker immunity.

Travel mode-related attributes

The impacts of the travel mode-related attributes on travel choice behaviour were largely different before and after the outbreak of COVID-19 pandemic. Our results confirm that attributes such as travel cost, waiting time, and travel distance that significantly affect travel mode choice behaviour under normal circumstances do not show any significance after the outbreak.

Table 3 presents the estimation results of travel mode-related attributes. It turns out that the only significant attribute is crowdedness in the metro and the bus. Specifically, an uncrowded public space in the metro and the bus can increase the probability of people choosing the metro (0.1121) and the bus (0.1279). This means that an uncrowded space would increase people's confidence to public transit. Although previous studies [18–19] state that crowdedness in public transit has a negative impact, in this case we believe that the significance of crowdedness is more likely to reflect people's concerns about being infected during the crowded public space.

4.2 Results from latent class MNL model

In this study, we used a latent class MNL model to capture the heterogeneity of people' preferences toward travel modes. The latent class MNL model includes two parts: membership function and utility function. In detail, travel mode-related attributes and pandemic-related attributes were introduced into utility functions while personal and household-related attributes were introduced into membership functions to describe the latent classes.

First, the number of latent classes need to be determined. *Table 4* shows the results when the latent class MNL models with different number of latent classes converge, from which it can be seen that when the number of latent classes equals 3, the BIC values is the lowest (5537.30). Therefore, the number of latent classes is set to 3 in this study. The ρ^2 of the final model is 0.3809, which is satisfactory and is greater than the value of the MNL model (ρ^2=0.2420) in the sub-section 4.1. The improvement of the latent class MNL model indicates that considering the heterogeneity of people's preferences can help better understand their travel mode choice behaviour.

Table 4 – BIC values for latent class MNL models with different number of classes

	LL	ρ^2	BIC	Number of parameters
S = 2	-2565.743	0.3299	5723.16	74
S = 3	-2328.888	0.3809	5537.30	110
S = 4	-2266.624	0.3879	5700.61	146

In the final estimation results, there are a total of 16 significant parameters, eight in the membership functions and eight in the utility functions. In general, conclusions from the latent class MNL model are similar to those from the MNL model. For instance, most travel mode-related attributes such as travel cost and waiting time, which have a significant impact on travel mode choice in a context before the COVID-19 pandemic, have no significant impact at all in the context of the COVID-19 pandemic. The following presents the details of the final estimation results from the latent class MNL model.

Table 5 – Estimation results of the utility parameters (p-value) in the latent class MNL model

High-susceptible class (Latent class 1)				Medium-susceptible class (Latent class 2)				Low-susceptible class (Latent class 3)			
Car	Taxi	Metro	Bus	Car	Taxi	Metro	Bus	Car	Taxi	Metro	Bus
Wuhan daily confirmed cases											
---	-0.0564 (0.457)	-0.1571 (0.001)	-0.1618 (0.001)	---	-0.0386 (0.393)	-0.0957 (0.064)	-0.0678 (0.314)	---	-0.0252 (0.704)	0.0089 (0.747)	0.0105 (0.781)
Wuhan currently confirmed cases											
---	-0.0213 (0.187)	-0.0280 (0.004)	-0.0113 (0.149)	---	-0.0042 (0.751)	-0.0157 (0.217)	-0.0082 (0.569)	---	0.0072 (0.517)	0.0100 (0.144)	0.0053 (0.577)
Other cities daily confirmed cases											
---	-0.0468 (0.576)	-0.0510 (0.210)	-0.0819 (0.046)	---	-0.0938 (0.311)	-0.1148 (0.169)	-0.0877 (0.411)	---	0.0215 (0.726)	0.0404 (0.128)	0.0494 (0.189)
Other cities currently confirmed cases											
---	-0.0033 (0.693)	-0.0200 (0.057)	-0.0062 (0.407)	---	0.0013 (0.872)	-0.0019 (0.821)	0.0054 (0.640)	---	0.0063 (0.486)	-0.0009 (0.878)	0.0033 (0.708)
Other cities daily deaths											
---	-0.0359 (0.440)	-0.1241 (0.014)	-0.0946 (0.016)	---	0.0490 (0.568)	-0.0353 (0.692)	0.0710 (0.417)	---	-0.0357 (0.474)	-0.0298 (0.202)	-0.0153 (0.659)
Vaccinated											
---	0.3660 (---)	0.7195 (---)	0.5541 (---)	---	0.3252 (---)	0.7128 (---)	0.5730 (---)	---	-0.4679 (---)	-0.1519 (---)	-0.0362 (---)

Not vaccinated											
---	-0.3660 (0.072)	-0.7195 (0.001)	-0.5541 (0.011)	---	-0.3252 (0.187)	-0.7128 (0.006)	-0.5730 (0.061)	---	0.4679 (0.078)	0.1519 (0.329)	0.0362 (0.811)
Crowdedness in metro and bus											
---	---	-0.0880 (---)	-0.0461 (---)	---	---	-0.3181 (---)	-0.2167 (---)	---	---	-0.0526 (---)	-0.0884 (---)
No crowdedness in the metro and bus											
---	---	0.0880 (0.481)	0.0461 (0.706)	---	---	0.3181 (0.001)	0.2167 (0.191)	---	---	0.0526 (0.482)	0.0884 (0.420)
Travel time											
---	-0.2044 (0.000)	-0.1020 (0.000)	-0.0482 (0.000)	---	0.1032 (0.000)	0.0564 (0.000)	0.0515 (0.001)	---	-0.1113 (0.000)	-0.0008 (0.938)	-0.0157 (0.242)

Pandemic-related attributes

From the above analysis, the number of classes in the latent class MNL model can be determined. The characteristics between the different classes will be stated below. *Table 5* presents the estimation results of case number-related attributes.

Latent class 1 shows the highest sensitivity to the COVID-19-related attributes. Daily cases in Wuhan significantly impact bus (-0.1618) and metro (-0.1571) choices, both lower than the reference car (0.0000). Current cases in Wuhan and other cities, as well as death cases in other cities, negatively affect public transit choices. Latent class 2 demonstrates moderate sensitivity, with Wuhan's daily cases negatively impacting metro choice (-0.0957). Latent class 3 shows no significant impact from the COVID-19 attributes. Vaccination status significantly influences mode choices for classes 1 and 2, with unvaccinated individuals reluctant to use public transit. Class 1 shows the strongest effect for the metro (0.7195), followed by the bus (0.5541) and taxi (0.3660). Interestingly, unvaccinated individuals in class 3 prefer taxis to cars, possibly due to lower driver's license ownership.

The analysis reveals three distinct groups based on the COVID-19 sensitivity: "high-susceptible" (class 1), "medium-susceptible" (class 2) and "low-susceptible" (class 3). Daily cases in Wuhan emerge as the most influential factor for classes 1 and 2, suggesting heightened concern about the local pandemic conditions. The pandemic generally decreases preferences for public transit, likely due to infection concerns in crowded spaces. Vaccination status significantly impacts mode choices, particularly for the more susceptible groups, highlighting its role in travel behaviour during the pandemic. These findings underscore the varied impacts of COVID-19 on different population segments and the importance of targeted strategies in transportation planning and public health measures.

Travel mode-related attributes

The estimation results of the alternative-specific attributes are shown in *Table 5*. In terms of the degree of crowdedness in public transit, the results tell that the medium-susceptible class is more sensitive to the congestion degree of the metro. When the space of public transit is uncrowded, the corresponding preferences of people in the medium susceptible class increase (0.3181). However, there are no significant differences between preferences of the high-susceptible and the low-susceptible classes, and their preferences toward crowdedness are lower than those of the medium-susceptible class.

In terms of travel time, it is significantly affecting the travel mode choice behaviour of people in the high-susceptible and medium-susceptible classes. For the high-susceptible class, car (0.0000) becomes the most preferred travel mode as the travel time increases. In terms of other modes, taxi is the most negatively affected (-0.2044), the metro is the second (-0.1020) and the bus is the least affected (-0.0482). This may be because the safety level of taxi travel is lower than that of car, but the price is higher than that of public transit, so it shows the most negative preference.

Meanwhile, *Table 5* shows that when the travel time increases, the medium-susceptible class is most inclined to take a taxi (0.1032), followed by the metro (0.0564), the bus (0.0515) and the car (0.0000) in sequence. From the following analysis about the characteristics of latent classes, we can conclude that people who currently use taxi the most and car/metro the least for travel. Therefore, it is reasonable to guess that people in this class may not own a private car. If this can be accepted, then the above conclusion is straightforward.

Personal and household-related attributes

Table 6 – Estimation results of membership parameters in the latent class MNL model

	High-susceptible class (Latent class 1)		**Medium-Susceptible class (Latent class 2)**		**Low-susceptible class (Latent class 3)**	
Personal-related attributes						
Gender						
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Male (reference)	-0.3117	---	-0.2700	---	0.0000	---
Female	0.3117	0.0962*	0.2700	0.1808	0.0000	---
Age						
18~24 (reference)	-0.0391	---	0.7872	---	0.0000	---
25~30	-0.7164	0.0228**	0.2411	0.5653	0.0000	---
31~40	-0.1858	0.5594	-0.0076	0.9870	0.0000	---
41~50	-0.1682	0.6735	-1.9887	0.0348**	0.0000	---
≥ 51	1.1095	0.1131	0.9680	0.2296	0.0000	---
Driver's license						
Yes (reference)	0.6155	---	0.3811	---	0.0000	---
No	-0.6155	0.0032***	-0.3811	0.1120	0.0000	---
Income trend						
Increase (reference)	0.6783	---	0.5942	---	0.0000	---
Stable	0.7309	0.0035***	1.0013	0.0084***	0.0000	---
Decrease	-1.1089	0.0066***	-0.1891	0.7035	0.0000	---
Wave	-0.3003	0.5097	-1.4064	0.1079	0.0000	---
Frequency of public transit						
Never（reference）	0.3292	---	-0.5338	---	0.0000	---
Seldom	0.1556	0.6005	-0.2276	0.5117	0.0000	---
Often	-0.2105	0.4642	0.0101	0.9788	0.0000	---
Every day	-0.2744	0.5141	0.7512	0.0637*	0.0000	---
Most frequently used mode currently						
Bus（reference）	-0.9282	---	-0.3226	---	0.0000	---
Metro	-0.9988	0.0063***	-1.0696	0.0074***	0.0000	---
Taxi	1.1142	0.1898	2.3369	0.0043***	0.0000	---
Car	0.8128	0.1162	-0.9448	0.1315	0.0000	---

Household-related attributes						
Household size						
	Estimate	p-value	Estimate	p-value	Estimate	p-value
1~2（reference）	-0.0458	---	-0.0379	---	0.0000	---
3~4	-0.6130	0.0321**	0.1684	0.6303	0.0000	---
5~6	-0.3148	0.4689	-0.1965	0.7092	0.0000	---
≥7	0.9737	0.1096	0.0660	0.9283	0.0000	---
Monthly household income						
≤¥10,000（reference）	-0.4783	---	0.3037	---	0.0000	---
(¥10,000,¥20,000]	-0.1519	0.5573	-0.0691	0.8116	0.0000	---
(¥20,000,¥30,000]	-0.4787	0.1429	-0.6001	0.1715	0.0000	---
>¥30,000	1.1089	0.0037***	0.3655	0.4130	0.0000	---
Distance from metro station to home						
<500m (reference)	-0.4726	---	-0.0761	---	0.0000	---
(500m, 1,000m]	-0.2317	0.3735	-0.3383	0.2845	0.0000	---
(1,000m, 1,500m]	0.0691	0.8506	-0.0664	0.8712	0.0000	---
＞1,500m	0.6352	0.0624*	0.4809	0.1969	0.0000	---

In the latent class MNL model, the personal attributes and household attributes of the respondents are used to describe the specific characteristics of the three latent classes. In the membership function, this paper uses the latent class of “low-susceptible class” as the reference, its corresponding parameter estimates are set to 0. The model estimation results of personal attributes are shown in *Table 6*.

The latent class analysis revealed distinct personal and household characteristics across susceptibility classes. Gender, age and transportation habits emerged as significant factors. Females showed a higher probability of belonging to the high-susceptible class (0.3117) compared to medium (0.2700) and low (0.000) classes. Age stratification indicated that individuals over 30 were more likely to fall into the low-susceptible category (0.0000), with notable differences in the 41–50 age group for medium susceptibility (-1.9887) and 25–30 for high susceptibility (-0.7164).

Transportation-related variables exhibited clear patterns. Possession of a driver’s license correlated with high susceptibility (0.6155). Public transit usage frequency was associated with different susceptibility levels: rare users tended towards high susceptibility (0.3292), while daily users aligned more with medium susceptibility (0.7512). The most frequently used travel mode also provided insights, with infrequent public transit users more likely to be in high or medium-susceptible classes. Frequent taxi users showed a propensity for medium susceptibility (2.3369), possibly due to lack of private vehicle access.

Household attributes also played a role in susceptibility classification. Notably, household size inversely correlated with high susceptibility, with larger households (more than 5 members) more likely to fall into this category compared to smaller ones (1–2 members: -0.0458; 3–4 members: -0.6130). In terms of monthly household income, those with a monthly household income greater than 30,000 yuan are more likely to be in the high-susceptible class (1.1089). Monthly household income less than 10,000 yuan is more likely to belong to the medium-susceptible class (0.3037). This means that compared to the high-susceptible and medium-susceptible classes, people with a monthly household income ranging from 10,000 to 30,000 have the highest probability of belonging to the low-susceptible class. Third, people living farther away from metro stations (greater than 1,500 m) were more likely to belong to the high/medium-susceptible classes (0.6352/0.4809).

Based on the model results, the average proportion of each latent class across sample can be obtained, as shown in *Table 7*. On average, the high-susceptible class accounts for the largest proportion (47.54%), the medium-susceptible class accounts for 20.79% of the sample and the low-susceptible class accounts for the lowest proportion (31.67%). It can be seen that almost half of the sample is highly susceptible to travelling during the COVID-19 pandemic. Nearly 70% of the sample are affected by the COVID-19 pandemic and only 30% of the sample are not easily affected.

Table 7 – Proportion of latent classes

Latent class	Proportion （%）
High-susceptible class	47.54
Medium-susceptible class	20.79
Low-susceptible class	31.67

5. SUMMARY AND DISCUSSION

Although we are already in the post COVID-19 era, research at different stages of the pandemic provides valuable insights for future large-scale epidemic prevention and control. In this sense, this paper tries to investigate the determinants and their degree of impact on travel modes choice behaviour under different stage of COVID 19. More precisely, a questionnaire based on a stated preference experiment about mode choices under the COVID-19 pandemic was dispensed and data was collected in Wuhan, China. Pilot survey was conducted to reduce the length and increase the quality of survey. An MNL model and a latent class MNL model were established and estimated. The results reveal the residents' travel mode preferences and their heterogeneity during the period of the COVID-19 pandemic.

This paper provides a different perspective to policy makers when they make policies. If the conclusions of this paper are acceptable, it can improve the implication of the COVID-19 prevention and control policies in the urban transportation system. First, this study reminds the managers that the attributes that impact people's travel mode choice behaviour were different before and after the outbreak of COVID-19 pandemic. For instance, attributes such as travel cost, transfer time or waiting time that significantly affect the residents' travel choice behaviour in a traditional situation became insignificant during the period of COVID-19 pandemic. Policies related to these attributes may be unable to increase the attractiveness of public transit. Second, widespread vaccination against COVID-19 could help to guide residents back into public transit. According to the results of the MNL model and the latent class MNL model, the attribute vaccination has the greatest impact on the choice of travel mode among the attributes related to the COVID-19 pandemic. From this point of view, compared to policies that reduce ticket fares, widespread vaccination against COVID-19 can more effectively improve the residents' confidence in public transit. Third, prevention policies need to reflect the differences among people. Different groups have different responses to the COVID-19 pandemic, and different prevention policies can more accurately control the epidemic. According to the latent class MNL model results, people with certain personal-related characteristics are more sensitive to the COVID-19, such as females, those aged over 30 and those with a household pre-tax income greater than 30,000 yuan. When regulatory policies are implemented within a certain group, surprising results may be achieved. For instance, if women can get vaccinated first, the travel demand for public transit may increase more quickly.

Although this study has made fruitful conclusions regarding the impact of the COVID-19 pandemic on the travel mode choice, there are still the following aspects that can be further studied in the future: First, the influence of latent factors on travel decisions under COVID-19 needs to be further explored. Although the existing literature has studied the influence of attitudes on travel behaviour under COVID-19, there is still a gap of attitude impacts on the travel mode choice in the context of China, especially in Wuhan city, where the COVID-19 first broke out. Second, this study focused only on travel mode changes due to COVID-19, but other impacts on the transit industry emerged from the pandemic, such as transit revenue and funding, which are important areas for future research.

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新冠疫情对出行方式选择行为的影响研究：以中国武汉市为例的陈述偏好案例研究

摘要

本文以中国武汉市为案例，研究了新冠疫情对出行方式选择行为的影响。问卷基于 SP 实验设计，调查在武汉市进行，并分别建立了 MNL 模型和潜在类别 MNL 模型。模型估计结果表明以下结论：首先，通常认为显著影响居民出行方式选择行为的属性在新冠疫情期间变得不显著。其次，年龄、性别、驾驶证、收入趋势、公共交通使用频率、当前最常使用的出行方式、家庭规模、家庭月收入、地铁站到居住地的距离、确诊/死亡病例数、疫苗接种等属性显著影响了受访者的出行偏好。第三，新冠疫情的爆发导致居民对公共交通的偏好下降，但疫苗的推广可以促使居民重返公共交通系统。第四，受访者被分为高敏感、中敏感和低敏感三个潜在类别。这些结论可为研究新冠疫情或其他类似公共卫生事件对交通系统的影响提供参考，并为政策制定提供支持，以此有效应对类似大规模传染病。

关键词

出行方式选择；新冠疫情；MNL 模型；潜在类别；武汉市