Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Role of latent factors and public policies in travel decisions under COVID-19 pandemic: Findings of a hybrid choice model

Chao Chen, Tao Feng, Xiaoning Gu

State Key Laboratory of Structural Analysis for Industrial Equipment, School of Automotive Engineering, Dalian University of Technology, Dalian 116024, PR China
Urban and Data Science, Graduate School of Advanced Science and Engineering, Hiroshima University, Higashi-Hiroshima 739-8511, Japan
Urban Planning and Transportation, Department of the Built Environment, Eindhoven University of Technology, Eindhoven 5600MB, the Netherlands

ARTICLE INFO

Keywords:
- Travel behavior
- Stated choice experiment
- COVID-19
- Hybrid choice model with panel effects
- Latent factors

ABSTRACT

Policy measures to control the spread of COVID-19 imposed by different countries have a devastating impact on people’s travel behaviors. Differing from the normal situation where general concerns on travel time and cost determine the travel choices, the uncertainty underlying behavior change in the case of a pandemic might be largely attributed to the latent aspects, i.e., social responsibility, risk perception, attitudes, which could diminish the effects of main attributes on travel decisions. Therefore, this paper examines the effects of COVID-19 related policies on individuals’ travel choices influenced by the latent aspects. A stated choice experiment was designed to collect people’s responses under policy measures to various transportation modes. Results of a hybrid choice model show that COVID-19 related policies significantly affect individuals’ transportation mode choice decisions during pandemic situations. The attributes, like travel time and travel cost, which significantly impact travel behavior in normal situations, become less relevant. Moreover, the travel preferences during the pandemic are significantly associated with latent factors of social responsibility, fear of infection, perceived risk, and travel anxiety. In general, public transportation is identified as an insecure alternative compared with other private modes, and people who are more socially responsible tend to travel less during the pandemic. Outcomes of this study could be of value to policymakers and public health emergencies, e.g., government authorities to utilize such knowledge in providing social support for these COVID-19 countermeasures and designing customized policies for specific population groups.

1. Introduction

Since the outbreak of COVID-19 in December 2019, the rapid spread of the pandemic has impacted many countries or regions with billions of people over the world (e.g., An, Lin, Li & He, 2021; Graham, Kremarik & Kruse, 2020). As of 1st March 2021, more than 115 million people have been infected by the COVID-19, and nearly 2.53 million among them died in the pandemic. Governments of different countries have imposed various control and preventive measures to control the virus’s spread. On one hand, these measures are expected to present an effective method to prevent and slow down the pandemic of diseases. On the other hand, the measures may also affect the development progress of sustainable cities in green transportation, e.g., increasing use of private cars and less public transportation. However, the practical effects depend on how society follows these rules. In any case, we must confess that the pandemic has multi-dimensional influences on human life, especially mobility and social interactions.

As one of the essential mobility options, public transportation receives no evidence that it increases the risk of infection and aggravates the spread of the epidemic; however, still restriction policies have been widely put forward, e.g., safe distance, face masks. These policies have delivered a blow to the public transportation sector. Taking the Netherlands as an example, the number of public transportation check-ins in 2020 decreased by up to 90% per day relative to the previous year.

Despite the various policy countermeasures to reduce social
interactions, people have various travel needs, and such trips range from daily shopping to commuting trips. The characteristics of such trips could also be remarkably different in different socio-demographic categories. These travel decisions could be affected by the severity of the pandemic and government policies. For passengers to safely use public transportation during the pandemic, many countries require the mandatory wearing of face masks and set a certain degree of reduction in the service capacity. Some latest research already indicated that COVID-19 had changed the attitudes in the use of public transportation, and people have become more in favor of private cars due to safety concerns (Eisenmann, Nobis, Kolarova, Lenz, & Winkler, 2021; Przybylowski, Stelmak & Suchanek, 2021). Therefore, examining the effects of policy measures of public transportation will provide a solid theoretical basis for the operators to establish targeted safe strategies and help restore public confidence in the service.

Recent studies have investigated the impacts of the pandemic on travel demands (e.g., Abdullah, Dias, Muyle & Shahn, 2020; Beck & Hemsher, 2020; Chan, Skali, Savage, Stadelmann & Torgler, 2020; Moslem et al., 2020; Parady, Taniguchi & Takami, 2020; Qu, Gao, & Li, 2020; Barbieri et al., 2021; Eisenmann, Nobis, Kolarova, Lenz, & Winkler, 2021; Przybylowski et al., 2021; Scorrano & Danielis, 2021; Shakiabi, De Jong, Alpkökin & Rashidi, 2021; van Wee & Witlox, 2021; Aadiitya & Rahul, 2021), from many different aspects such as behavior change, transportation modes, effects of the built environment, and psychological impacts. For example, Abdullah et al. (2020) analyzed travel behavior changes before and during the COVID-19 pandemic using data collected from multiple countries. Factors like gender, travel purpose, and pandemic-related policy measures (e.g., social distance, face-mask requirement) are found significant predictors of mode choice. Eisenmann, Nobis, Kolarova, Lenz, & Winkler (2021) investigated the change in transportation mode usage during a particularly restricted lockdown period in Germany. They found that people, in general, were less inclined to consider public transportation and bicycle as transportation modes, and one-third of people miss a car in the pandemic crisis for car-free households. For a detailed review of human mobility behaviors in the context of the current pandemic see Benita (2021).

These findings on the potential behavior change are interesting as they were drawn from the revealed observations. However, revealed data does not uncover the decision mechanism of individuals’ choice behavior underlying the latent factors, e.g., stress, perception, personality, awareness. Previous studies have acknowledged that risk-taking attitudes are critical in predicting reductions in human mobility (Abdullag et al., 2020; Chan et al., 2020); however, the effects of latent factors under the pandemic on travel decisions were not yet sufficiently examined (Aadiitya & Rahul, 2021). While latent attitudes in normal situations were generally found to enhance model interpretability, their role influencing travel behavior during the COVID-19 pandemic might be further enlarged because people may overtake decisions or fall into an unsafe situation unconsciously, which is largely dependent on their knowledge, opinions, and personal judgment. Therefore, the effects of individuals’ latent perspectives on travel behavior during a pandemic are significant and deserve further investigation.

This paper aims to identify the effects of policy measures and latent attitudes of people on their transportation mode choice. Considering the growing interest in implementing discrete choice models that encapsulate attitudes and opinions, a hybrid choice model (HCM), which simultaneously identifies the underlying latent factors from a set of observable attitudes and opinions and estimates their effects, is used. More specifically, we focus on the effects of public policy measures on the use of public transportation and the preference of private travel modes without sharing spaces that are potentially risky in an exposure. The data used in this paper is based on a stated choice experiment rather than a reveal preference survey because there is no unified data collection that goes back over a year for the various “stages” of policy and different transportation modes. To the best of our knowledge, this is the first attempt to utilize HCM in understanding travel preferences under the COVID-19 pandemic.

It is hoped that this study could enrich the growing literature in COVID-19 pandemic-related research and policy decision-making. First, the present paper represents a groundbreaking on investigating the travel behavior changes under the pandemic considering COVID-19 related policies and latent factors. Understanding travelers’ choice behavior changes could help public transportation operators and policymakers identify the drivers and barriers of a successful COVID-19 restriction policy. Second, this study employs a stated choice experiment to study such behavior changes. As we will discuss later in more detail, the estimation results share some similarities with the empirical analyses in the existing literature (Aadiitya & Rahul, 2021).

In the following sections, we first present the experimental design used in this paper and additional aspects of the data collection. Then, the implementation of a hybrid choice model with panel effects is elaborated. After that, the model estimation results will be discussed. Finally, the paper will be summarized with major findings and concluded with some policy recommendations for a post-COVID agenda.

2. Survey and experimental design

In this study, we set our research area in the context of the Netherlands. The Dutch government has announced various sets of policy measures since the first COVID-19 case confirmed in late February 2020, defined according to the different levels of severity and emergency call, i.e., “intelligent lockdown,” “hard lockdown,” and curfew. These policy measures are expected to present an effective method to prevent and slow down infection. Fig. 1 shows that the number of daily COVID-19 cases over the past year presents a clear wave (just along with the policy packages announced in The Netherlands). According to the government guidelines, Dutch public transportation operators also set rules to ensure travel safety, e.g., keeping a 1.5 m distance inside the bus, wearing a non-medical face mask, and increasing disinfection frequency. There is no doubt that these policies and measures have multi-dimensional influences on the travel behaviors of Dutch people.

To investigate how these COVID-19 related policies affect travel preferences, a Web-based questionnaire including a stated choice experiment was implemented. The first part of the questionnaire asks respondents about their socio-demographic characteristics and monthly travel patterns for different travel purposes before and during the pandemic. The second part is a stated choice experiment of transportation mode choice influenced by COVID-19 related policy measures and regulations. The last part of the survey relates to a set of attitude-related questions.

2.1. Attributes and attributes levels

In the stated choice experiment, respondents were asked to indicate which one of the five transportation modes they would like to choose, including car, bus, bike, shared E-bike, and walk. Besides, the option “not travel” was also included.

The literature indicates that activity-travel contexts play a crucial role in choice decisions (Swait et al., 2002; Molin & Timmermans, 2010). In this paper, the travel contexts were defined in terms of travel distance, travel purpose, and governmental policy on the COVID-19. Two travel distance scenarios are constructed for urban scales, namely a short-distance trip and a long-distance trip. The two representative trip distances (2.5 and 5 km) are representative to the citizens living in The Netherlands and commonly used in other previous studies (Arentze & Molin, 2013; van den Berg, Geurs, Visken & Arentze, 2018). Based on the statistical data published by the Dutch Ministry of Infrastructure and Water Management, the maximum walking distance that Dutch people could accept is 2.5 km, and approximately 90% of all bicycle trips are shorter than 5 km. Therefore, to make the survey scenarios realistic, 2.5 and 5 km were selected as the two levels of the contextual attribute,
travel distance. It is also important to note that the origins and destinations in the experiment are not fixed. In other words, all trips could originate from or terminate at arbitrary locations as long as the total distances are limited to 2.5 or 5 km.

Travel purpose is set to four levels that involves the mandatory and nonmandatory daily activities: work, shopping, leisure, and social. In addition, since the COVID-19 pandemic, a four-tier national alert system has been implemented, within which each tier alert corresponds to various levels of restrictions, influencing people’s activities and movement. Therefore, we include this national alert as a COVID-19 policy in the choice experiment. In practice, multiple rules were implemented concerning each level of the four-tier alerts. Here, we summarize the governmental measures for the four-tier alert system. Detailed explanations on the alert system were also provided in the survey before the choice experiment to help respondents better understand the context of the rules. Detailed descriptions can be found in Appendix A. Note that this travel context could implicitly consider the effects of the different severity of the pandemic.

Regarding alternative-specific attributes, the examination of the relevant literature suggests that the transportation mode choice is primarily affected by travel time, travel costs, out-of-vehicle time, and having seats or not (Guo, Feng & Timmermans, 2020). However, since the outbreak of COVID-19, traffic congestion has been drastically reduced (Arellana, Márquez & Cantillo, 2020; Tian, An, Chen & Tian, 2020; Cui et al., 2020). The data collected by the Dutch Rijkswaterstaat also shows a significant reduction in traffic congestions after the outbreak of COVID-19. Following the advice of the National Institute for Public Health and the Environment (RIVM), public transportation operators in the Netherlands are also taking measures to ensure travel safety, e.g., travelers are requested to wear a facemask on a bus and keep a distance of 1.5 m from each other. Finding a seat while traveling on the bus was not a problem during the pandemic. Therefore, in this paper, the effects of congestion time and seat availability were not considered. The specification of other attributes (e.g., travel cost, travel time, and out-of-vehicle time) and corresponding levels were then designed based on the current traveling situations (provided by Google Maps) and relevant cost calculator websites.

In addition to the attributes mentioned above, some unique factors regarding public transportation (i.e., the bus option in this paper) cannot be ignored. As discussed, some restrictions and measures have been applied for public transportation in the Netherlands. These measures can be briefly classified into five categories: limiting the number of onboard passengers, facemask requirement, enhanced cleaning, 1.5 m rule, and providing hand rubs. Therefore, to investigate the impacts of these measures on the choice of buses, five regulation-related attributes were also selected and shown to the respondents. The allowed percentage of the total number of seats was varied in terms of 4 levels. Facemask requirement, 1.5 m rule, and providing hand rubs were varied in terms of two levels, with and without regulations. Furthermore, the disinfection frequency in vehicles was specified with four levels, from the low frequency to a relatively high frequency. The setting of these COVID-19 related rules for public transportation is to provide participants with a mimic situation on the difference between a pandemic and normal situation. Table 1 summarizes the attributes and attribute levels involved in the experiment design.

It is important to point out that because of the set of attribute levels, this study is indeed confined to the context of The Netherlands. In addition, we must acknowledge that there are differences in urban size and the actions taken by the governments across different countries, which may lead to different travel patterns. We nonetheless observe that in many western countries (e.g., Britain, Sweden, and Germany), the urban size, lifestyle, and official COVID-19 countermeasures are similar to those held in The Netherlands (Mouratidis & Papagiannakis, 2021). Therefore, given the similarities between countries, we expect our results to hold lessons well beyond the Dutch context.

2.2. Experiment design

Given that the number of attributes and attribute levels is large, it is impossible to create a full factorial design ($4^5 \times 2^{13}$ profiles). Thus, an orthogonal fractional factorial design consisting of 64 profiles was

---

3. https://www.europeandataportal.eu/en/impact-studies/covid-19/covid-19-related-traffic-reduction-and-decreased-air-pollution-europe

4. https://www.numbeo.com/gas-prices/country_result.jsp?country=Netherlands

5. https://www.eur.nl/en/campus/locations/campus-woudenstein/parking/shared-scooters-and-e-bikes

6. https://www.bravo.info/english/tickets
created to reduce the number of choice tasks. The 64 profiles were then blocked into eight blocks of 8 choice tasks, and respondents were randomly allocated to one block after agreeing to take the survey. Fig. 2 shows an example of the choice task. It should be noted that, though many advanced experimental design strategies (e.g., D-efficient design, S-efficient design, and Bayesian efficient design, etc.) were proposed in the literature, these strategies require priors (i.e., information on the expected parameter estimates) in order to calculate the expected utilities for each of the alternatives within the design. When no prior information is available, an orthogonal design is more reliable. In addition, people’s preference under the pandemic may largely differ from common situations, e.g., safety concerns may override other factors, a prior value-based design would not offer apparent advantages. Therefore, in this paper, an orthogonal fractional factorial design was ultimately adopted.

### 2.3. Attitudinal statements

In addition to the choice experiment, several attitudinal statements/indicators were also collected as a part of the survey to measure the latent factors that may influence transportation mode choice in the pandemic. So far, a variety of latent factors, such as comfort, convenience, environment, have been studied with regard to their impacts on the transportation mode choice decisions. A review of those works and findings could be found in Bouscasse (2018). Nonetheless, these mostly considered attitudes or perceptions may become less important in the pandemic situation (Urban & Braun Kohlová, 2020). According to the results of an analysis in 58 countries by Chan et al. (2020), risk-taking attitudes are critical factors affecting human mobility in the pandemic. Some other pandemic-specific latent factors have also been examined in recent studies (Eisenmann, Nobis, Kolarova, Lenz, & Winkler, 2021; Scorrano & Danielis, 2021).

Because COVID-19 has infected more than two hundred million people worldwide, people may easily feel fear, panic, and anxiety (Luo & Lam, 2020). Based on an examination of relevant literature, we formulated twelve statements (indicators) to measure underlying latent factors that are assumed to be associated with travel decisions under the pandemic: social responsibility, travel anxiety, fear of infection, and the perceived risk (Azlan, Hamzah, Sern, Ayub & Mohamad, 2020; Abdulalah et al., 2020; Chan et al., 2020; He & Harris, 2020; Usher, Jackson, Durkin, Gyamfi & Bhullar, 2020). Social responsibility refers to the desire to be “responsible citizens” by complying with the COVID-19 countermeasures, while travel anxiety represents an emotional response to potential risks, e.g., people are exposed to the information of fatalities and infection rate of COVID-19, the degree of travel anxiety may increase accordingly. The fear of infection is to measure the level of fear about COVID-19, which may influence not only travel but also other behaviors. The perceived risk, which is regarded as a predictor of intentions and behavioral change, is used to explain the likelihood of

| Categories | Attributes | Levels |
|------------|------------|--------|
| Contexts   | COVID-19 restrictions policy | Totally open, Lockdown Tier 1: Medium alert, Lockdown Tier 2: High alert, Lockdown Tier 3: Very high alert |
| Travel distance (km) | Short distance—2.5 km, Long distance—5 km |
| Travel purpose | Work, Shopping, Leisure, Social |
| Car travel time (min) | 4, 6, 8, 10 (for 2.5 km); 10, 12, 14, 16 (for 5 km) |
| Travel cost (€) | 0.3, 0.5, 0.7, 0.9 (for 2.5 km); 0.6, 1, 1.4, 1.8 (for 5 km) |
| Bus travel time (min) | 6, 8, 12, 14 (for 2.5 km); 14, 16, 18, 20 (for 5 km) |
| Out-of-vehicle/Walking time (min) | 1, 3, 5, 7 |
| Travel cost (€) | 1, 1.2, 1.4, 1.6 (for 2.5 km); 1.6, 1.8, 2, 2.2 (for 5 km) |
| Allowed percent of the total number of seats | 100%, 75%, 50%, 25% of the total number of seats |
| Face mask required | Yes, No |
| Disinfection frequency | Every journey, once per 4 journeys, once per 8 journeys, once a day |
| Apply 1.5 m rule | Yes, No |
| Provide hand rubs | Yes, No |
| Bike travel time (min) | 6, 8, 10, 12 (for 2.5 km); 14, 16, 18, 20 (for 5 km) |
| Shared E-bike travel time (min) | 4, 6, 8, 10 (for 2.5 km); 12, 14, 16, 18 (for 5 km) |
| Travel cost (€) | 0.4, 0.6, 0.8, 1 (for 2.5 km); 1.2, 1.4, 1.6, 1.8 (for 5 km) |
| Walk travel time (min) | 20, 25, 30, 35 (for 2.5 km); 50, 55, 60, 65 (for 5 km) |

**Table 1** Attributes and attribute levels of the choice experiment.
engagement in health-promoting behavior in response to the use of public transportation. Table 3 lists the detailed statements related to these latent factors. In this survey, respondents were required to indicate their level of agreement using a five-point Likert scale (e.g., “strongly disagree,” “somewhat disagree,” “neither disagree nor agree,” “somewhat agree,” and “strongly agree”) for a series of 12 statements. The five-point Likert scale was chosen because this type of Likert scale is commonly used in the literature and is easy for analysis.

3. Data collection

Respondents were recruited through face-to-face invitations and social media to cover the individuals who have limited internet access or are tech-savvy. However, due to the restriction of COVID-19 policies, it is challenging to manage face-to-face surveys. Instead, we invited volunteers to present the questionnaires to their family members, especially the seniors. The volunteers actually share an assistant role because the questionnaire is available online, respondents are not bound to the physical locations to participate in the survey. The other part of the survey presented on social media was through posts and messages on Facebook. We believe that social media has been used more frequently during the pandemic. The rapidly growing monthly active users of Facebook also confirm our assumption (Ahmed et al., 2020). In addition, to reduce the potential bias in the data observation, a random sample was drawn. Several controls on the characteristics of respondents were also implemented such that the sample is representative of the Dutch population. In particular, the data collection was completed after several waves, and each wave was followed by data analysis of the sample’s characteristics.

The invited respondents were presented with the research purpose and the data protection policy. Before starting the formal survey, they were asked to provide their basic socio-demographics (e.g., gender, age, and education level) to make sure the socioeconomic indicators of the sample are representative of the population. To ensure the scope of the study, only the people who live in major cities of the Netherlands were recruited.

The data were gathered from 15 December 2020, the day in which Dutch Prime Minister Mark Rutte informed the public at a 19-minute press conference that the Netherlands will enter a hard lockdown for the following five weeks. This is also when The Netherlands has the strictest measures against the COVID-19. Note that in mid-January 2021, after the data were collected, the Dutch government held another press conference to extend the lockdown period till 15 March. During the time of lockdown, a total of 684 respondents were invited to participate in the survey. Of these, 568 respondents agreed to engage in, and finally, 394 completed, and valid surveys were received.

3.1. Socio-demographics and attitudinal indicators

The descriptive statistics of the socio-demographic variables are summarized in Table 2. It shows that 49.2% of respondents in the survey are males, while the remaining 50.8% are females. Concerning age, the sample stated a high share of respondents between 26 and 35 years old (almost 26.1%), whereas 17% of the respondents were between 18 and 25 years old, 18.8% were between 36 and 45 years old, and 38.1% were older than 46 years old. It suggests that people participating in the survey are younger than average. The distribution of marital status shows that singles make up 67% of the sample, while couples without children represent 25.6%, only 7.4% of the respondents have one or more children.

Moreover, almost 71% of the respondents have received higher education. Finally, most respondents have a full-time job, while about 14.8% have a part-time job. The remainder either has no job or retired. In general, this profile has a relatively good mix of gender and education level but an under-representation of the elderly. However, considering the scope of this study is on the general population, the sample is considered feasible in representing the Dutch society to study their transportation mode choice behaviors in the COVID-19 pandemic.

The distribution of the sample and descriptive summary statistics of the 12 statements are summarized in Table 3. It can be seen that respondents in the Netherlands do not have much worry about the risk of getting infected by COVID-19 (I1 and I2) and are less likely to feel anxious and pressured while traveling (I3 and I4). In contrast, respondents are particularly concerned about travel safety in the pandemic and have a high social responsibility (I5 to I12).

3.2. Travel intensities before and during the COVID-19 pandemic

The data on monthly activity-travel patterns for various travel purposes before and during the COVID-19 pandemic was also collected. Table 4 provides several statistical indicators for the six activities chosen to be investigated in the survey. It could be clearly observed that respondents in the Netherlands traveled less during the COVID-19 pandemic. The most notable change is commuting. One reason is that the Dutch employees are being encouraged or forced to work from home in the pandemic. Besides, most indoor venues like bars, restaurants, sports halls were closed, leading to decreased travel demands for social contacts, leisure, and recreational activities. It is worth mentioning that the travel frequency for picking up or sending children to school activities has a slight variation (from 0.88 to 0.55). This may be because Dutch primary schools have been open except for the two hard lockdowns. However, there is a particular deviation between the results analyzed in this paper and the reality because only a small proportion of participants have one or more children (as indicated in Table 2). It is necessary, therefore, to elaborate more the effects of COVID-19 on primary education and parents in further study if the data is available.

Table 2

| Characteristic         | Level                      | Percentage (%) | Dutch census (%) |
|------------------------|----------------------------|----------------|------------------|
| Gender                 | Male                       | 49.2           | 49.5             |
|                        | Female                     | 50.8           | 50.6             |
| Age                    | [18, 25]                   | 17             | 14.7             |
|                        | [26, 35]                   | 26.1           | 15.3             |
|                        | [36, 45]                   | 18.8           | 14.1             |
|                        | [46, 55]                   | 20.8           | 16.9             |
|                        | ≥56                        | 17.3           | 39               |
| Education level        | HAVO/VWO or below          | 28.7           | 30.6             |
|                        | HBO/VO (bachelor)          | 33.2           | 37.4             |
|                        | Master or higher           | 38.1           | 32               |
| Marital status         | Single                     | 67.0           | –                |
|                        | Couple without children    | 25.6           | –                |
|                        | Couple with one child      | 2.0            | –                |
|                        | Couple with more than one  | 5.4            | –                |
|                        | child                      |                |                  |
| Employer type          | Unemployed/retired         | 10.3           | –                |
|                        | Part time job              | 14.8           | –                |
|                        | Full time job              | 74.9           | –                |

* A total of 394 respondents were included in the analysis.

4. Hybrid choice model with panel effects

To simultaneously investigate the transportation mode choice behavior in the context of the COVID-19 pandemic, an HCM is specified incorporating COVID-19 regulations-related attributes, alternative-specific attributes, and the latent factors of individual persons. HCM is essentially an extension of classical discrete choice models that includes attitudinal variables into the utility function. The model has been applied in many studies, e.g., transportation mode choice, electric vehicle purchases, car-sharing, and transportation policy development (e.g., Kamargianni, Ben-Akiva & Polydoropoulou, 2014; Chorus & Kroesen, 2014; Jin, Yao, & An, 2020).

Basiclly, HCMs incorporate a latent variable model to improve the
choosing a transportation alternative consists of four components, latent factors and requires a measurement model representing the hypothesized causal relationships between latent factors and the attitudinal indicators. Based on the framework of random utility theory, the utility of choosing a transportation alternative consists of four components, including travel context of choice situation, the alternative-specific attributes, COVID-19 regulations-related attributes, and the latent factors, which can be defined as follows.

\[ U_{ins} = \beta_i^A X_{ins}^A + \beta_i^B X_{ins}^B + \beta_i^C X_{ins}^C + \epsilon_{ins} \]  

(1)

where \( U_{ins} \) represents the utility of individual \( n \) choosing alternative \( i \) in choice situation \( s \). \( X_{ins}^A \) is a vector \((A \times 1)\) of attributes describing the travel context of choice situation \( s \); \( X_{ins}^B \) is a vector \((P \times 1)\) of attributes related to COVID-19 regulations; \( X_{ins}^C \) is a vector \((L \times 1)\) of latent factors of individual \( n \). The vectors \( \beta_i^A, \beta_i^B, \beta_i^C \), and \( \epsilon_{ins} \), respectively, are parameters that need to be estimated. \( \epsilon_{ins} \) represents a random disturbance term for alternative \( i \) in choice situation \( s \). Because each respondent made a series of choices (i.e., a block of choice sets), panel effects should also be considered. Therefore, to deal with the serial correlation within an individual (i.e., the panel effect), the random disturbance term \( \epsilon_{ins} \) is defined as follows.

\[ \epsilon_{ins} = \beta_i^0 + \eta_{ins} + \zeta_{ins} \sim N\left(0, \sigma_{\eta}^2\right), \zeta_{ins} \sim G\left(0, \sigma_{\zeta}^2\right) \]  

(2)

where \( \beta_i^0 \) is an alternative-specific constant. To reflect the panel effect, \( \eta_{ins} \) is assumed to be an error component that is individual specific. This random component varies across individuals but is invariant over different choice situations for the same individual. In addition, it is assumed that \( \eta_{ins} \) follows a normal distribution with zero mean and standard deviation \( \sigma_{\eta} \). Lastly, the random disturbance term, \( \zeta_{ins} \), is assumed to be independently and identically Gumbel distributed across transportation alternatives, individuals, and choice situations with standard deviation \( \sigma_{\zeta} \).

Table 3 presents the modeling framework of the proposed HCM, including the latent factors and corresponding indicators. Four latent factors, as presented previously in Section 2, are included. These latent factors are assumed to be related to the socio-demographical characteristics of individuals. The structural relationship between the latent factors and socio-demographics, therefore, could be defined as follows:

\[ X_{n}^l = \delta^l + \delta^l X_{n}^A + \xi^l \sim N\left(0, \sigma^l_{\xi} \right) \]  

(3)

where \( X_{n}^l (X_{n}^l \in X_{n}^B) \) is the \( l \)th latent factor of individual \( n \). \( X_{n}^A \) is a vector \((D \times 1)\) of the selected socio-demographics of individual \( n \). \( \delta^l \) represents a vector of unknown parameters connecting the socio-demographics with the \( l \)th latent factor. \( \xi^l \) indicates a random disturbance term, and in this paper, is assumed to be normally distributed with \( \delta^l \) mean and standard deviation \( \sigma_{\xi} \).

As we will discuss later in more detail, the specification of the HCM corresponds well with the results of the factor analysis (Table 6). Note that the indicators revealing latent factors were coded using a five-Likert scale. Thus, it is supposed that each indicator is represented by an ordinal scale of measurement. The measurement relationships between the latent factors and corresponding indicators could be estimated using ordered probit models. The mathematical expression is defined as follows.

\[ I_u^v = \theta^A X^A_n + \epsilon^v \sim N\left(0, \sigma^v_{\epsilon} \right) \]  

(4)

\[ I_{P}^l = \begin{cases} 
1. & I_{P}^l \leq I^l_{\xi} \\
2. & I^l_{\xi} < I_{P}^l \leq I^l_{\tau} \\
\vdots \\
b. & I^l_{\tau_{n-1}} < I_{P}^l \leq I^l_{\tau} \\
B. & I^l_{\tau} < I_{P}^l 
\end{cases} \]  

(5)
where $I_{kn}^*$ represents the latent and continuous variable in terms of the $k$th observed and ordinal indicator $I_{kn}$. It consists of two key components, the linear combination of latent factors $X_Ln$ and unknow parameters $\theta_k$, and the normally distributed error term $\epsilon_k$. $\theta_k$ is a vector of $(1 \times L)$ binary variables, in which the $l$th position of $\theta_k$ is set as 1 if the $l$th latent factor is related to the $k$th indicator, otherwise 0. As shown in Eq. (5), $I_{kn}$ is an integer in a band of 1 to $B$, indicating that individual $n$ would select the $b$th ordinal indicator for the $k$th indicator if $I_{kn}^*$ lies in the range between $\tau_{kb}^1$ and $\tau_{kb}^2$. Note that the cut-off parameters $\tau_{kb}$ ($b = 1, \ldots, B$) are to be estimated, such that:

$$\tau_{kb}^1 \leq \cdots \leq \tau_{kb}^{B-1} \leq \tau_{kb}^B$$ (6)

As the measurements are using a Likert scale with $B = 5$ levels, 4 parameters $\psi_i$ need to be defined and estimated. In order to account for the symmetry of the indicators, this paper defined two positive parameters $\psi_1$ and $\psi_2$, instead of 4 different parameters. Then, the cut-off parameters could be defined as:

$$\tau_{kb}^1 = \psi_1 - \psi_2$$

$$\tau_{kb}^2 = \psi_1$$

$$\tau_{kb}^3 = \psi_2$$

$$\tau_{kb}^4 = \psi_1 + \psi_2$$ (7)

Finally, assuming that the random disturbance terms are independent across transportation alternatives and choice situations, the joint likelihood function of the proposed model for individual $n$ could be defined as follows.

$$\mathcal{L}_n = \int f_{X_Ln}(x_{Ln}) \prod_{k \neq l} f_{X_k}(x_{kn}) \prod_{a} f_{X_A}(a, \pi, \sigma) \prod_{b} f_{X_k}(x_{kn}) \prod_{\nu} f_{Y}(y_{kn} | \pi, \sigma, \theta, \tau) \prod_{\alpha} f_{I}(I_{kn}^* | \rho, \sigma) \prod_{\omega} f_{L}(L_{kn}^* | \delta, \omega) \, dx_{Ln}$$ (8)

where $f_{X_Ln}()$ is the likelihood function of the choice model part considering panel effects, $f_{X_k}()$ represents the likelihood function of the measurement relationship in the latent variable model part (e.g., the

---

**Table 4**

Statistics on the number of activities a month.

| Statistic | BE | DU |
|-----------|----|----|
| Grocery shopping | 8.63 | 6.25 |
| Work office | 13.90 | 5.66 |
| Casual social contacts | 6.00 | 2.40 |
| Leisure with low energy consumption | 1.96 | 0.42 |
| Leisure with high energy consumption | 1.07 | 0.35 |
| Recreation | 6.97 | 3.93 |
| Pick-up or send children to school | 0.88 | 0.55 |

Note: BE is short for before the pandemic; DU is an abbreviation for during the pandemic; SD represents standard deviation; MAD means median absolute deviation.

---

Fig. 3. The modeling framework for the proposed HCM.
likelihood function of the ordered probit model in this paper). \( f_1(\cdot) \) denotes the likelihood function of the structural relationship in the latent variable model part. The corresponding expressions of the three likelihood functions are defined as follows.

\[
f_1(\cdot) = \prod_{i=1}^{n} \prod_{s=1}^{k} \left[ P_{m(i)} \left( \begin{array}{c} X_i^C, X_i^L, X_i^P \end{array} \right) \right] \quad (9)
\]

\[
f_2(\cdot) = \prod_{i=1}^{n} \prod_{s=1}^{k} \Phi \left( \frac{X_i^C - \delta_i - \delta_i X_i^L}{\sigma_i} \right) \quad (10)
\]

\[
f_3(\cdot) = \prod_{k=1}^{K} \frac{1}{\sigma_d} \Phi \left( \frac{X_i - \delta_k - \delta_k X_i^L}{\sigma_d} \right) \quad (11)
\]

where \( \eta_{ns} \) is a proxy variable denoting the choice outcome of an individual, which equals 1 if individual \( n \) chooses alternative \( i \) in choice situation \( s \), or 0 otherwise. \( \eta_{ns} \) is also a proxy and binary variable representing the attitudinal indicator \( f_3 \), which is 1 if individual \( n \) presents the \( n \)th Likert scale value for the \( k \)th attitudinal indicator, or 0 otherwise. \( 
\Phi(\cdot) \) is the standard normal probability density function (PDF). \( 
\Phi(\cdot) \) represents the cumulative distribution function (CDF) of the standardized normal distribution. \( P_{m(i)}(\cdot) \) indicates the probability that transportation alternative \( i \) is chosen by individual \( n \) in choice situation \( s \). With the assumption that the error terms are identically and independently extreme value type I distributed across choice alternatives and the decision rule of decision-makers is utility maximization, \( P_{m(i)}(\cdot) \) can be written as:

\[
P_{m(i)} = \exp (\beta_i^0 + \beta_i X_i^C + X_i^L + X_i^P) \quad (12)
\]

Because of the involvement of integrals, Eq. (9) does not take on a closed-form solution. Therefore, in this paper, the maximum simulated likelihood method is employed to estimate the parameters. Instead of using exact probabilities, the maximum simulated likelihood method exploits the average results by simulating probabilities (see Train, 2009, for more details). Then, the simulated likelihood function of the proposed model can be represented as:

\[
Z_{r} = \frac{1}{R} \sum_{r=1}^{R} f_1(\eta_{ns}) f_2(\eta_{ns}) f_3(\eta_{ns}) \quad (13)
\]

where \( R \) denotes the total number of draws from the standard normal density function. \( \hat{X}_i^C \) and \( \hat{X}_i^L \) respectively represent the simulated latent factors and panel effects in terms of the \( r \)th draw. In particular, the random draws in this paper were generated by using scrambled Halton draws.

5. Results discussion

5.1. Mode choice behaviors under different COVID-19 restrictions policies

The results obtained from the choice experiment could be analyzed for potential mode market shares and mode choice shifts under different COVID-19 restrictions policies. As discussed in Section 3, a total of 394 samples with 3152 observations were finally collected. Fig. 4 illustrates the general mode choices of the sample under different COVID-19 restrictions policies with or without the inclusion of not traveling. The findings in Fig. 4 are consistent with the results of attitudinal indicators provided in Table 3. It can be observed from Fig. 4(a) that more respondents choose to stay at home with the increased levels of lockdown tiers (regardless of travel purposes), and the proportion rose to the highest (e.g., about 36 percent) when the alert moves to the highest level, tier 4. It is also interesting to observe that bike is the most attractive alternative in the Netherlands, even without the COVID-19 outbreak. This result confirms our common knowledge that cycling is still the most popular form of daily transportation with the outbreak of the COVID-19 (as shown in Fig. 4(b)).

Fig. 4 also shows that fewer people are willing to use public buses as the lockdown tier grows. This result corresponds well with previous studies that there is a compatible agreement on the decline in public transportation ridership since the outbreak of COVID-19 (Bucksy, 2020; Moslem et al., 2020; Gibbs et al., 2020). However, similar to the findings in a prior study (Shakibasi et al., 2021), it is interesting to note that not many public transportation users shift their mode to the private transportation mode, car. As shown in Fig. 4(b), the car’s share increased by nearly 5 percent from the open to lockdown tier 1, indicating that people prefer to use the safer private mode, car, at the early stage COVID-19 pandemic. However, the changes in these mode shifts became obvious as the pandemic continued. Lastly, results show that not much has changed for the mode shares of the walk and shared E-bike over different lockdown tiers. In recent years, E-bike-sharing has rapidly emerged in the Netherlands, and the demand has grown substantially (de Kruifj, Etema, Kamphuis & Dijst, 2018; Sun, Feng, Kemperman & Spahn, 2020). However, the stringent lockdown has severely hindered the surge in the number of users. Because of the need for sharing with strangers, using the shared E-bike may increase infection risk. This result confirms that the COVID-19 outbreak presents great challenges to the sustainability of shared mobility (Shokouhyar, Shokouhyar, Sobhani & Gorizi, 2021).

5.2. Analysis of latent factors

The first step in building the HCM is to define the latent factors involved. Efforts in the existing literature to identify these hypothetical relationships are often based on exploratory factor analysis (EFA). Therefore, this paper first employs an EFA to identify the underlying latent factors from a set of indicators. The identified latent constructs are then adopted as a measurement model of the latent variable model part of the HCM. Simultaneously integrating the discrete choice model and latent variable model, the effects of the latent factors and other observed attributes in the utility functions of choice alternatives can be finally estimated.

Table 5 presents the EFA results, indicating that the 12 attitudinal indicators could be reduced to 4 latent factors. In particular, these four factors accounted for about 73% of the variance among the 12 indicators listed in Table 3. The corresponding factor loadings used to reveal the strength and direction of an indicator on a factor are also summarized in Table 6. It should be noted that, although several rules have been developed in the literature to determine the number of factors in the EFA, it is indeed difficult to judge which rule is the best. Consequently, selecting the number of extracted factors becomes a subjective exercise. In this manuscript, we are of the opinion that reasonable interpretability is a crucial factor in determining the number of factors when the purpose is to generate behavior insights. In addition, based on the results presented in Table 6, the extracted factors have no multiple explanations for the indicators. Thus, we believe selecting the four latent factors is appropriate in this study. As indicated, factor 1, representing the social responsibility under the COVID-19 pandemic, is associated with five correlated indicators. Factor 2 consists of 3 positive indicators representing the perceived risk of using public transportation. Factors 3 is associated with two indicators that express the fears over the COVID-19 (as shown in Fig. 4(b)).

Finally, two indicators on travel anxiety constitute factor 4. Therefore, a total of 4 latent factors are identified in this paper: \( \text{fear of infection} \), \( \text{perceived risk} \), \( \text{travel anxiety} \), and \( \text{social responsibility} \).
5.3. Results of HCM

Using the sample of 3152 choice sets, the HCM was estimated. The model estimation was implemented in Python language on Jupyter Notebook 6.0.1 and performed using the most recent version of the Python package Biogeme (Bierlaire, 2020). Before estimating the model, all categorical attributes were effect coded, using the last category of each attribute as the reference category (Wu, Cao & Huting, 2018).

Table 7 shows the estimation results of the final model specification for the discrete choice model part. Results of a basic Multinomial Logit (MNL) model are also provided for comparison. Overall, the estimated HCM has a good fit and fits the data significantly better than the basic MNL model. The log-likelihood value increased from $-4430.98$ to $-3450.7$. The HCM improves the adjusted Rho-squared from 0.211 for the basic MNL model to 0.386. This result is expected, given that HCM included additional potential influencing attributes. However, it should be noted that the improvement in model fit cannot be entirely attributed to the model considering latent factors since the HCM also takes the panel structure of the data into consideration, whereas the basic MNL model does not. In addition, the parameter signs for both the HCM and basic Multinomial Logit model are almost the same. Furthermore, compared with the basic Multinomial Logit model, attributes are less statistically significant for the HCM. Because the HCM performs better than the Multinomial Logit model, we discuss the results by focusing mainly on the HCM.

Travel contexts

First of all, the travel contexts (i.e., COVID-19 restrictions policies and travel purposes) are generally found to affect travel choices significantly. The results reveal that people generally tend to go out rather than stay at home when there is no lockdown or the lockdown tier is low. When the lockdown tier is raised to a higher level (i.e., the lockdown tiers 2 and 3), stopping travel becomes the preferred option. In addition, the parameter of the lockdown tier 3 ($=1.11$) is higher than the parameter of lockdown tier 2 ($=0.457$), indicating that the escalating lockdown level does influence the travel decisions differently. In the case of travel purposes, results show that people still prefer working in the office relative to telecommuting in the pandemic. It may imply that physical interactions with colleagues play an essential role in daily works. Conversely, they seem more reluctant to have social and leisure activities because of the high infection risk. Furthermore, shopping has a negative effect on the decision of not traveling, which means people

Table 5

Results of the factor analysis: total explained variance.

| Factors | Initial eigenvalues | Extraction sums of squared loadings | Cumulative% | Rotation sums of squared loadings | Cumulative% |
|---------|---------------------|-------------------------------------|-------------|--------------------------------|-------------|
|         | Total | Total % of variance | Cumulative% | Total | % of variance | Cumulative% |
| 1       | 6.060 | 3.507 | 29.229 | 29.228 | 3.396 | 28.304 |
| 2       | 1.963 | 3.217 | 26.810 | 56.039 | 2.159 | 17.988 |
| 3       | 1.001 | 1.408 | 11.737 | 67.776 | 1.713 | 14.271 |
| 4       | 0.649 | 0.671 | 5.592 | 73.368 | 1.537 | 12.805 |
| 5       | 0.437 |             |     |             |     |     |
| 6       | 0.409 |             |     |             |     |     |
| 7       | 0.374 |             |     |             |     |     |
| 8       | 0.272 |             |     |             |     |     |
| 9       | 0.255 |             |     |             |     |     |
| 10      | 0.250 |             |     |             |     |     |
| 11      | 0.181 |             |     |             |     |     |
| 12      | 0.150 |             |     |             |     |     |

Note: Extraction method: Maximum likelihood; Extraction criteria: eigenvalue > 1; Rotation method = Varimax with Kaiser Normalization.

Table 6

Attitudinal statements and factor loadings.

| Indicators/Statements | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
|-----------------------|----------|----------|----------|----------|
| $I_1$                 | -        | -        | 0.688    | -        |
| $I_2$                 | -        | -        | 0.985    | -        |
| $I_3$                 | -        | -        | -        | 0.624    |
| $I_4$                 | -        | 0.664    | -        | -        |
| $I_5$                 | 0.695    | -        | -        | -        |
| $I_6$                 | 0.794    | -        | -        | -        |
| $I_7$                 | 0.751    | -        | -        | -        |
| $I_8$                 | 0.679    | -        | -        | -        |
| $I_9$                 | 0.816    | -        | -        | -        |
| $I_{10}$              | 0.880    | -        | -        | -        |
| $I_{11}$              | 0.727    | -        | -        | -        |

Note: (1) Only factors loadings higher than 0.6 are retained and “-” represents factor loadings lower than 0.6; (2) F1: Social responsibility; F2: Perceived risk; F3: Fear of infection; F4: Travel anxiety.

5.3. Results of HCM

Using the sample of 3152 choice sets, the HCM was estimated. The model estimation was implemented in Python language on Jupyter Notebook 6.0.1 and performed using the most recent version of the Python package Biogeme (Bierlaire, 2020). Before estimating the model, all categorical attributes were effect coded, using the last category of each attribute as the reference category (Wu, Cao & Huting, 2018). Table 7 shows the estimation results of the final model specification for the discrete choice model part. Results of a basic Multinomial Logit (MNL) model are also provided for comparison. Overall, the estimated HCM has a good fit and fits the data significantly better than the basic MNL model. The log-likelihood value increased from $-4430.98$ to $-3450.7$. The HCM improves the adjusted Rho-squared from 0.211 for the basic MNL model to 0.386. This result is expected, given that HCM included additional potential influencing attributes. However, it should be noted that the improvement in model fit cannot be entirely attributed to the model considering latent factors since the HCM also takes the panel structure of the data into consideration, whereas the basic MNL model does not. In addition, the parameter signs for both the HCM and basic Multinomial Logit model are almost the same. Furthermore, compared with the basic Multinomial Logit model, attributes are less statistically significant for the HCM. Because the HCM performs better than the Multinomial Logit model, we discuss the results by focusing mainly on the HCM.

Travel contexts

First of all, the travel contexts (i.e., COVID-19 restrictions policies and travel purposes) are generally found to affect travel choices significantly. The results reveal that people generally tend to go out rather than stay at home when there is no lockdown or the lockdown tier is low. When the lockdown tier is raised to a higher level (i.e., the lockdown tiers 2 and 3), stopping travel becomes the preferred option. In addition, the parameter of the lockdown tier 3 ($=1.11$) is higher than the parameter of lockdown tier 2 ($=0.457$), indicating that the escalating lockdown level does influence the travel decisions differently. In the case of travel purposes, results show that people still prefer working in the office relative to telecommuting in the pandemic. It may imply that physical interactions with colleagues play an essential role in daily works. Conversely, they seem more reluctant to have social and leisure activities because of the high infection risk. Furthermore, shopping has a negative effect on the decision of not traveling, which means people
the pandemic, as one could expect. The result is consistent with most negatively associated with the probability of all transportation modes in physical grocery shops, which are normally easier to access. This is perhaps Note: SEB means shared E-bike. ***

Table 7
Results of the discrete choice model part.

| Attribute | Transportation mode | HCM Estimate | t-value | MNL Estimate | t-value |
|-----------|---------------------|--------------|---------|--------------|---------|
| Travel context | COVID-19 restrictions policy | Not travel | 1.07*** 14.1 | 1.11*** 13.8 |
| | Lockdown Tier 2 | Not travel | 0.426*** 5.23 | 0.457*** 5.35 |
| | Lockdown Tier 1 | Not travel | -0.244*** -2.64 | -0.262*** -2.73 |
| | Totally open | Not travel | -1.252 | -1.305 |
| Travel Purpose | Work | Not travel | -0.209*** -2.45 | -0.015*** -3.04 |
| | Social | Not travel | 0.237*** 2.91 | 0.139* 1.73 |
| | Shopping | Not travel | -0.181** -2.16 | -0.236*** -2.82 |
| | Leisure | Not travel | 0.153 | -0.112 |
| Alternative-specific attribute | Travel cost ($) | Car, Bus &SEB | -0.178** -2.16 | -0.319* -1.76 |
| | Travel time (min) | All modes | -0.304*** -6.15 | -0.353*** -7.37 |
| | Out-of-vehicle time (min) | Bus | -0.335 | -1.12 -0.252 -0.83 |
| | Face mask required | Bus | 0.00875 0.129 | 0.0245 0.353 |
| | Apply 1.5 m rule | Bus | -0.0488 | -0.721 0.19* 1.72 |
| | Provide hand rubs | Bus | -0.0381 | -0.562 -0.021 -0.453 |
| | Allowed number of passengers (%) | 25% of the total seats | Bus | 0.16 | 1.44 0.16* 1.684 |
| | | 50% of the total seats | Bus | 0.0579 0.503 | 0.088 0.529 |
| | | 75% of the total seats | Bus | -0.0448 | -0.375 -0.044 -0.257 |
| | | 100% of the total seats | Bus | -0.1731 | - |
| Disinfection frequency | Every journey | Bus | 0.138 | 1.23 0.144 1.27 |
| | | Once per 4 journeys | Bus | 0.19* 1.72 | 0.192* 1.72 |
| | | Once per 8 journeys | Bus | -0.198 | -1.55 -0.502** -2.15 |
| | Once a day | Bus | -0.13 | - | -0.137 |
| Alternative-specific constants | Social responsibility | Not travel | - | - 1.48*** 2.82 |
| | Perceived risk | Bus | - | -1.94* -1.93 |
| | Fear of infection | Car | - | 1.91*** 3.28 |
| | | Bus | - | -0.006 -0.009 |
| | | Bike | - | -0.747 | -1.54 |
| | | SEB | - | 3.54** 2.53 |
| | | Walk | - | 1.57** 2.13 |
| Travel anxiety | Car | - | - | -0.455 -1.29 |
| | | Bus | - | 0.07 | 0.11 |
| | | Bike | - | -0.774** 2.31 |
| | | SEB | - | -0.456 | -0.816 |
| | | Walk | - | 0.008 0.223 |
| Standard deviation of the random panel effect parameter | Car | - | - | 0.387 0.771 |
| | Bus | - | - | -1.88** -2.27 |
| | Bike | - | - | 0.264 0.554 |
| | SEB | - | - | -0.725 -0.782 |
| | Walk | - | - | 0.274 0.481 |
| Goodness-of-fit indexes | Log-likelihood value at zero | -5647.6 | -5647.6 |
| | Log-likelihood value at convergence | -4430.98 | -3450.7 |
| | $\rho^2$ | 0.215 | 0.389 |
| | Adjusted $\rho^2$ | 0.211 | 0.386 |

Note: SEB means shared E-bike. *** p-value < 0.01, ** p-value < 0.05 and * p-value < 0.1 refer to the confidence level at 99%, 95% and 90%, respectively.

tend to visit physical stores instead of shopping online. This is perhaps because online shopping cannot acquire the same convenience as physical grocery shops, which are normally easier to access.

Alternative-specific attributes

Regarding the alternative-specific attributes, results reveal that the common contributing factors (e.g., travel time and travel cost) are negatively associated with the probability of all transportation modes in the pandemic, as one could expect. The result is consistent with most previous studies that travel time and travel cost are crucial in choosing a transportation mode (Sun et al., 2020; Aaditya & Rahul, 2021). Although studies (Guo et al., 2020; Luan, Yang, Jiang & Wang, 2021) have suggested that out-of-vehicle time has a negative impact on the choice of public transportation, it is interesting to note here that the parameter in this study is statistically insignificant.

The effects of COVID-19-related regulations applied in public transportation on mode choice behavior have also been investigated, and several interesting findings could also be generated from the results.

The allowed number of passengers represents the maximum number of passengers carried per bus. A consensus is that a higher number of passengers in an enclosed area represents a higher risk of infection with COVID-19 (Shelat, Cats, & van Cranenburgh, 2021). Related policies, therefore, have been designed to lower the passenger capacity. We can see that when the maximum number of passengers carried per bus is beyond 75 percent of the seating capacity, the parameter is negative, which means that travelers are less likely to use buses. However, if the maximum number of passengers carried per bus is less than 75 percent of the seating capacity, travelers believe buses are safe and reliable for traveling. This restriction has a positive and significant effect, especially when the allowed number of passengers is 25% of the total seats.

Moreover, the estimated parameters are positive for high disinfection frequencies and negative for low disinfection frequencies. We can see that when the disinfection frequency is greater than or equal to once per 8 journeys, the parameters are statistically significant and negative. However, when the disinfection frequency reaches once per 4 journeys, the parameters become positive. The results are understandable because high-frequency disinfections would be a massive boost for travelers to use public buses in the COVID-19 pandemic. Furthermore, results show
that though the estimates for wearing a facemask are not statistically significant, the sign is found to be positive, indicating the requirement for wearing a facemask also has a positive effect on the choice of the public bus.

Latent factors

The results also show that the identified latent factors significantly influence transportation mode choice behavior. The factor of social responsibility in the pandemic tends to be positively associated with the probability of not traveling. It means people who are more socially responsible are more likely to stay at home than go out. In addition, the results reveal that people who attach more importance to the perceived risk of using public transportation tend not to use buses, which is in line with the results of previous studies (e.g., Bucky, 2020; de Haas, Faber, & Hamersma, 2020; Hynes & Malone, 2020). Furthermore, the estimated parameters for fear of infection and travel anxiety represent the effects of the two latent factors on the probabilities of various transportation modes for traveling relative to the reference alternative of ‘not travel’. The fear of infection is positively associated with using private cars and shared E-bikes, as well as walking. It means that people who perceived the severity of the COVID-19 are more likely to use private vehicles or walk for traveling rather than staying at home in the pandemic. Surprisingly, the fear of infection is negatively associated with the probability of using bikes. However, this parameter is statistically insignificant. Lastly, the results reveal that people who are prone to feel anxious in the pandemic are more likely to use a bike for traveling.

Alternative-specific constants

The positive values of the alternative-specific constants (ASCs) of car, bike, shared E-bike, and walking show that the sampled respondents, on average, are still prone to travel rather than stay at home. In general, these ASCs capture the residual mean influences of the unobserved attributes on the choice associated with their respective alternatives. The outbreak of the COVID-19 raises public health concerns on traveling due to its possible infection. The statistically significant values of these ASCs, to a certain extent, can reflect these concerns. Though the estimated ASC of the alternative bus is statistically insignificant, the sign of this parameter is still in line with theoretical expectation, indicating that people, in general, are unwilling to use mass public transportation in the COVID-19 pandemic.

The estimation results of the structural relationship in the latent variable model part are presented in Table 8. It can be observed that several socio-demographics have a significant impact on these latent factors. To be specific, females have a higher tendency to be anxiety-inducing, have a social responsibility to prevent the spread of the virus, pay closer attention to safety while traveling, and generate a deeper fear of COVID-19 infection than males. In addition, older people tend to be less concerned than the younger generation about travel safety. This is unfortunate as COVID-19 normally influences older people more seriously (Lithander et al., 2020; Bajaj et al., 2021). Moreover, young people are more afraid of being infected by COVID-19 and more likely to feel anxious while traveling than older people. The results also show that educational level tends to be positively associated with perceived risk, travel anxiety, and social responsibility, indicating that people with a higher educational level can be more concerned about travel safety, higher travel anxiety, and high social responsibility.

Furthermore, people who have kids tend to be more afraid of the COVID-19 than those who have no children. On the other hand, single and couples without children are more likely to have a strong sense of social responsibility and preferences for travel safety and anxiety. Lastly, as expected, employed respondents tend to attach more importance to social responsibility and travel safety than those who were unemployed or retired.

Table 9 shows the results of the measurement relationship in the latent variable model part. The constants and measurement parameters for the first indicator of each latent factor were fixed as 0 and 1, respectively. By normalizing these parameters, the remaining parameters in the latent variable models could be identified. As indicated in Table 9, all parameters are significant at the 1% confidence level. Besides, most indicators show a positive relationship with the corresponding latent factors, indicating that a higher score for the indicator question tends to increase the likelihood of respondents having a higher recognition of the corresponding latent factors. In contrast, the indicators $P_1$, $P_2$, and $P_3$ are negatively associated with social responsibility, which means that, though respondents have a strong sense of social responsibility and are willing to take specific measures to prevent the spread of the COVID-19, they still want to go out from home.

6. Conclusions and discussion

Public transportation plays a key role in urban sustainability, reducing congestion and ambient pollutants. The diminishing trend of using public transportation induced by COVID-19 is a serious concern relevant to the strategic development of sustainable cities because any transformation back to the use of private cars is ultimately unacceptable. Actually, the issue of promoting the use of public transportation is not only a concern of service operators but also an issue of the whole society, which is how to recover the confidence of people in traveling with public transportation. This demands the need to further understand people’s decision-making in transportation mode choice under different COVID-19 policy countermeasures.

Taking a hybrid choice modeling framework as a basis, in this paper, we have presented the results of an empirical study investigating transportation mode choice behavior during the COVID-19 pandemic. Using the stated preference data collected in the Netherlands, this study provides a profound insight into travel choice behavior in the context of the COVID-19 pandemic. Furthermore, the findings could also serve as a valuable source of information for governments to implement effective policies to slow down the spread of COVID-19 and improve public transportation services.

| Socio-demographics | Latent attitudes | | | |
|---------------------|--|--|--|--|
| Gender (1: female, | 0.148*** | 0.106*** | 0.0524** | 0.253*** |
| Age (years) | 0.0047 | -0.0177*** | -0.0321** | -0.0421*** |
| Education (1: HAVO/ | 0.13*** | 0.197*** | -0.0469 | 0.275*** |
| Marital status | | | | |
| Employer type | | | | |
| Constant | 0.726*** | 0.575*** | 0.227* | 0.438** |
| Standard deviation | 2.99 | 3.12 | 2.31 | 3.3 |

Note: Values in parentheses represent t-statistics; *** p-value < 0.01, ** p-value < 0.05 and * p-value < 0.10 refer to the confidence level at 99%, 95% and 90%, respectively.
First, it is found that the willingness to travel during the pandemic, in general, is diminished. People choose to stay at home and do not travel unless the journey is essential. It is also interesting to note that travel behaviors under the pandemic are remarkably different from regular daily lives. Dutch people generally do not expect to use public transportation under the COVID-19 pandemic. Instead, transportation modes with non-shared spaces become the preferred choices for traveling. These results also correspond well with the recent studies (Abdullah et al., 2020).

Second, results show that the COVID-19 related restrictions policy significantly impacts the likelihood of ‘not travel’, which increases by upgrading the level of lockdown tiers. It implies that the Dutch government restrictions on mobility, in general, have contributed to reducing travel demand and slowing down the spread of COVID-19. However, it is interesting to note that the probability of choosing travel is still high in lockdown tier 1. Besides, the most notable difference between lockdown tier 1 and tier 2 is whether these commercial and recreational facilities (e.g., restaurants and bars) are open. These results suggest that closing recreational facilities should be given a high priority in developing travel restriction policies.

Third, compared to the intelligent lockdown policies that play a significant role in affecting travel preferences, the traditional attributes (e.g., out-of-vehicle time), which primarily affect the transportation mode choice in ordinary situations, become insignificant. Therefore, the implicit trade-offs made by the Dutch population could be inferred. This means, during the pandemic period, waiting time is less relevant to influence transportation mode choices relative to the risk of COVID-19 infection. This is perhaps an important indication in the sense that the latent factors in the choice models that are traditionally considered more explorable to understand behavior become more important in the context of the COVID-19 pandemic to determine or predict transportation mode choices.

Forth, our results indicate that the reduction in public transportation usage is mainly attributed to government policies. The protective measures adopted by Dutch public transportation operators, such as 1.5 m social distance rules and the requirement of wearing a face mask, conversely cannot fully lift the spirits of consumers to use public transportation. Besides, more emphasis is placed on the low passenger load factor in the pandemic. Therefore, policymakers need to make choices between a moderately easy policy and a continued loss-making public transportation operation.

Lastly, the findings associated with the latent factors show that the considered latent factors have a significant effect on the transportation mode choice decision. The results show that people who are more socially responsible tend to follow the government requirements and travel less during the pandemic. The estimate of the latent factors of travel anxiety and perceived risk suggests that people perceive public transportation as an insecure option for traveling compared with other more private modes. In this context, designing more effective policies and protective measures (on top of the current policies) may be a strategy for the public transportation operators to regain travelers’ trust.

Though the present study provides insights into the impacts of COVID-19 related government policies on transportation mode choice behavior, several elaborations could also be considered in future studies. First, the stated preference data may raise questions regarding the generalizability of the results according to the actual behavior. Future studies may therefore elaborate the actual behavior using revealed preference data. Second, although the survey was completed based on combining random sampling from both social media and face-to-face interviews, the samples are not bias-free and possibly overrepresent a specific group of people. Thus, a more balanced sample would extend its generality. Third, this study only considered trips being made with purposes, while the undirected trips (without purposes) are also being popularly addressed in the literature, especially during the COVID-19 pandemic (Hook, De Vos, Van Acker & Witlox, 2021). Thus, it could be interesting to include undirected trips in future research. Fourth, the findings are applicable to the city scales in the Dutch contexts (e.g., 2.5 and 5 km), while the difference in compliance behavior because of the spatial settings, different culture and mobility patterns may lead to different policy responses, especially in the less developed areas where buses are essential and challenging to keep social distancing.

Lastly, policy countermeasures are highly featured with the timing. The survey data were collected during the period when vaccination was still underdeveloped (the first COVID-19 vaccination in the Netherlands

---

### Table 9

| Latent attitudes | Indicator | Constant | Measurement parameter | $\psi_1$ | $\psi_2$ | Cutoff parameters | $b = 1$ | $b = 2$ | $b = 3$ | $b = 4$ |
|-----------------|----------|---------|-----------------------|-------|-------|------------------|-------|-------|-------|-------|
| Fear of infection | $I^1$ | 0 | 1 | 0.297 | 0.862 | $-1.16$ | $-0.30$ | 0.86 | 1.16 |
| | $I^2$ | (-0.65) | 0.634 | (10.4) | (9.62) | $-1.11$ | (21.6) | (31.9) | $-0.30$ | 0.86 | 1.16 |
| Travel anxiety | $I^3$ | 0 | 1 | 0.28 | 1.11 | $-1.39$ | $-0.28$ | 1.11 | 1.39 |
| | $I^4$ | (-0.731) | 0.848 | (-15.6) | (20.8) | $-1.85$ | (25.9) | (35.6) | $-0.42$ | 1.43 | 1.85 |
| Perceived risk | $I^5$ | 0 | 1 | 0.415 | 1.43 | $-1.85$ | $-0.42$ | 1.43 | 1.85 |
| | $I^6$ | 0.633 | 1.22 | (11.8) | (23.6) | $-1.85$ | (25.9) | (35.6) | $-0.42$ | 1.43 | 1.85 |
| | $I^7$ | 0.574 | 1.24 | (11.8) | (26.4) | $-1.85$ | (25.9) | (35.6) | $-0.42$ | 1.43 | 1.85 |
| Social responsibility | $I^8$ | 0 | 1 | 0.36 | 0.96 | $-1.32$ | $-0.36$ | 0.96 | 1.32 |
| | $I^9$ | (-0.525) | (-0.535) | (-8.97) | (-8.97) | $-1.32$ | $-0.36$ | 0.96 | 1.32 |
| | $I^{10}$ | -0.754 | -0.754 | (-8.85) | (-8.85) | $-1.32$ | $-0.36$ | 0.96 | 1.32 |
| | $I^{11}$ | 0.377 | 0.377 | (5.73) | (5.73) | $-1.32$ | $-0.36$ | 0.96 | 1.32 |
| | $I^{12}$ | -0.777 | -0.777 | (-8.94) | (-8.94) | $-1.32$ | $-0.36$ | 0.96 | 1.32 |

Note: Values in parentheses are t-statistics, and all estimates are statistically significant ($p$-value < 0.01).
was given on January 8, 2021\(^7\), while at the time when we finished the analysis, vaccination has been put forward in different extent in some countries including the Netherlands. The differences in the behavior induced by the vaccination for different people definitely deserve further understanding. However, despite of the various potential of further studies, we hope the current study could offer an initial reference for smart policy decision-making to effectively tackle the challenges in the COVID-19 pandemic.

**Appendix A. Description of the COVID-19 restrictions policy**

| Category                  | Lockdown Tier 1: Medium alert                                                                 | Lockdown Tier 2: High alert                                                                 | Lockdown Tier 3: Very high alert |
|---------------------------|------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|----------------------------------|
| **Work**                  | Work from home, unless it is absolutely necessary that you go to work.                           | Work from home, unless it is absolutely necessary that you go to work.                           | Work from home, unless it is absolutely necessary that you go to work.            |
| Meeting friends and family| 1. At home you may have no more than 3 visitors per day.                                        | 1. At home you may receive no more than 2 people per day.                                        | 1. At home you should receive no more than 2 visitors aged 13 or over per day.    |
|                           | 2. The maximum group size outdoors and indoors (except in your home) is 4 people from different households. | 2. The maximum group size outdoors and indoors (except in your home) is 2 people from different households. | 2. Only go outdoors alone, with members of your household or in a group of no more than 2 people. |
| Education                 | In secondary and higher education institutions (VO, MBO, and HO) everyone must wear a face mask outside lessons. | In secondary schools, MBO schools, and institutions for higher education (HBO and universities) everyone must wear a face mask except during lessons. | Primary and secondary schools, schools for secondary vocation education (MBO), and higher education institutions (universities and HBO) are closed. |
| Bars, pubs, and restaurants| All establishments that serve food and drinks are open.                                         | All establishments that serve food and drinks must remain closed.                                | All establishments that serve food and drinks must remain closed.                |
| Indoor leisure            | All venues, including museums, theatres, sex establishments, cinemas, amusement parks, zoos, swimming pools, and libraries, are open. | All venues, including museums, theatres, sex establishments, cinemas, amusement parks, zoos, swimming pools, and libraries, are closed. | Take-away will still be possible. Venues such as museums, theatres, amusement parks, zoos, casinos, saunas, indoor sporting venues, and establishments serving food and drink (including in hotels) are closed. |
| Shops                     | 1. Stores are open but must close no later than 20:00. There will be no late-night shopping.     | 1. Stores are open but must close no later than 20:00. There will be no late-night shopping.     | Venues such as museums, theatres, amusement parks, zoos, casinos, saunas, indoor sporting venues, and establishments serving food and drink (including in hotels) are closed. |
|                           | 2. Locations where contact-based professions are carried out, such as hairdressers, nail salons, and sex establishments, are open. | 2. Locations where contact-based professions are carried out, such as hairdressers, nail salons, and sex establishments, are closed. | Take-away will still be possible. Venues such as museums, theatres, amusement parks, zoos, casinos, saunas, indoor sporting venues, and establishments serving food and drink (including in hotels) are closed. |
| Travel                    | 1. Stay at home as much as possible.                                                            | 1. Stay at home as much as possible.                                                            | 1. You are strongly advised to work from home.                                  |
|                           | 2. Avoid non-essential travel.                                                                 | 2. Avoid non-essential travel.                                                                 | 2. Do not book any foreign travel and do not travel abroad.                     |
|                           | 3. If you go on holiday, stay in or near your holiday accommodation as much as possible.      | 3. If you go on holiday, stay in or near your holiday accommodation as much as possible.      | 3. Locations where contact-based professions are carried out, such as hairdressers, nail salons, and sex establishments, are closed. |
|                           | 4. Limit the number of outings and avoid busy places.                                           | 4. Limit the number of outings and avoid busy places.                                           | 3. Public transportation is for essential travel only.                           |

---

**References**

Aaditya, B., & Rahul, T. M. (2021). Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach. *Transport Policy, 108*, 47–58.

Abdullah, N., Dias, C., Muley, D., & Shablin, M. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives, 8*, Article 100255.

Ahmed, N., Shabkha, T., Shamim, A., Khan, K. S., Hussain, S. M., & Uman, A. (2020). The COVID-19 infodemic: A quantitative analysis through facebook. *Cureus, 12*(11).

An, Y., Lin, X., Li, M., & He, F. (2021). Dynamic Governance decisions on multi-modal inter-city travel during a large-scale epidemic spreading. *Transport Policy.*

Arentze, T. A., & Molin, E. J. (2013). Travelers’ preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice, 58*, 15–28.

Azlan, A. A., Hamzah, M. R., Sern, T. J., Ayub, S. H., & Mohamad, E. (2020). Public knowledge, attitudes and practices towards COVID-19: A cross-sectional study in Malaysia. *PloS One, 15*(5), Article e0233668.

Bajaj, V., Gadi, N., Spithman, A. P., Wu, S. C., Choi, C. H., & Moulton, V. R. (2021). Aging, immunity, and COVID-19: How age influences the host immune response to coronavirus infections? *Frontiers in Physiology, 11*, 1793.

Barbieri, D. M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Leesa, D. A., et al. (2021). Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PloS One, 16*(2), Article e0245886.

---

\(7\) https://www.rivm.nl/en/news/first-covid-19-vaccination-on-8-january-2021

**Declaration of Competing Interest**

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

**Acknowledgments**

This research was supported by the China Scholarship Council (No. 20190660030).
Beck, M. J., & Hemph, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia: the early days of easing restrictions. Transport Policy, 99, 95–919.

Benita, F. (2021). Human mobility behavior in COVID-19: A systematic literature review and bibliometric analysis. Sustainable Cities and Society, 70, Article 102916.

Bierlaire, M. (2020). A short introduction to pandaloiogic: Transport and Mobility Laboratory, ENAC. EPFL. Technical report TRANSP-OR 200605.

Boucasse, H. (2018) Integrated choice and latent variable models: A literature review on mode choice. Working Papers 2018-07, Grenoble Applied Economics Laboratory (GAEL).

Bucks, P. (2020). Modal share changes due to COVID-19: The case of Budapest. Transportation Research Interdisciplinary Perspectives, 8, Article 100141.

Chan, H. F., Skall, A., Savage, D. A., Stadelmann, D., & Tørgler, B. (2020). Risk attitudes and human mobility during the COVID-19 pandemic. Scientific Reports, 10(1), 1–13.

Chorus, C. G., & Kroesen, M. (2014). On the (im-) possibility of deriving transport policy implications from hybrid choice models. Transport Policy, 36, 217–222.

Cui, Z., Zhu, M., Wang, S., Wang, P., Zhou, Y., Cao, Q., Kopca, C. & Wang, Y. (2020). Traffic performance score for measuring the impact of COVID-19 on urban mobility. arXiv preprint arXiv:2007.00648.

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch ‘intelligent lockdown’ change activities, work and travel behaviour: Evidence from longitudinal data in the Nethelands. Transportation Research Interdisciplinary Perspectives, 6, Article 100150.

de Kruifj, J., Ettema, D., Kamphuis, C. B., & Djipt, M. (2018). Evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands. Journal of Transport & Health, 10, 74–83.

Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., & Winkler, C. (2021). Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. Transport Policy, 103, 60–67.

Gibbs, H., Liu, Y., Pearson, C. A., Jarvis, C. I., Grundy, C., Quilty, B. J., et al. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. Nature Communications. https://doi.org/10.1038/s41467-020-18783-0

Graham, A., Kremarik, F., & Kruse, W. (2020). Attitudes of ageing passengers to air travel since the coronavirus pandemic. Journal of Air Transport Management, 87, Article 101865.

Guo, J., Feng, T., & Timmermans, H. J. (2020). Co-dependent workplace, residence and commuting mode choices: Results of a multi-dimensional mixed logit model with panel effects. Cities, 96, Article 102448 (London, England).

He, H., & Harris, L. (2020). The impact of COVID-19 pandemic on corporate social responsibility and marketing philosophy. Journal of Business Research, 116, 176–182.

Hook, H., De Vos, J., Van Acker, V., & Witlox, F. (2021). Does undirected travel compensate for reduced directed travel during lockdown? Transportation Letters, 13 (5–6), 414–420.

Hynes, M., & Malone, P. (2020). The utility of public transport in Ireland: Post COVID-19 lockdown and beyond. UCD Geary Institute for Public Policy. Public Policy.ie, 1st June. https://www.ucd.ie/epflgip/public-policy/public-policy-ie/components/public-policy-programme/transport/research/impact-of-covid-19-lockdown-and-beyond/

Jin, F., Yao, E., & An, K. (2020). Understanding customers’ battery electric vehicle sharing adoption based on hybrid choice model. Journal of Cleaner Production, 258, Article 120764.

Kamargianni, M., Ben-Akiva, M., & Polyloropoulou, A. (2014). Incorporating social interaction into hybrid choice models. Transportation, 41(6), 1263–1285.

Lithander, F. E., Neumann, S., Tenison, E., Lloyd, K., Welsh, T. J., Rodrigues, J. C., et al. (2020). COVID-19 in older people: A rapid clinical review. Age and Ageing, 49(4), 501–515.

Luan, S., Yang, Q., Jiang, Z., & Wang, W. (2021). Exploring the impact of COVID-19 on individual’s travel mode choice in China. Transport Policy, 106, 271–280.

Luo, J. M., & Lam, C. F. (2020). Travel anxiety, risk attitude and travel intentions towards “Travel Bubble” destinations in Hong Kong: Effect of the fear of COVID-19. International Journal of Environmental Research and Public Health, 17(21), 7859.

Molin, E. J., & Timmermans, H. J. (2010). Context dependent stated choice experiments: The case of tram egress mode choice. Journal of Choice Modelling, 3(1), 39–56.

Moslem, S., Campisi, T., Szmelter-Jaronski, A., Duda, S., Nahiduzzaman, K. M., & Tesoriere, G. (2020). Best–worst method for modelling mobility choice after COVID-19: Evidence from Italy. Sustainability, 12(17), 6824.

Mouradidé, K., & Papagiannakis, A. (2021). COVID-19, internet, and mobility: The rise of teleswork, telehealth, e-learning, and e-shopping. Sustainable Cities and Society, 74, Article 103182.

Parady, G., Taniguchi, A., & Takami, K. (2020). Travel behavior changes during the COVID-19 pandemic in Japan: Analyzing the effects of risk perception and social influence on going-out self-restriction. Transportation Research Interdisciplinary Perspectives, 7, Article 100181.

Przybylowksi, A., Stelmak, S., & Suchanek, M. (2021). Mobility behaviour in view of the impact of the COVID-19 pandemic: public transport users in Galanek: case study. Sustainability, 13(1), 364.

Scorreno, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. Research in Transportation Economics, Article 101031.

Shahbazi, S., De Jong, G. C., Alkpkin, P., & Rashidi, T. H. (2021). Impact of the COVID-19 pandemic on travel behavior in Istanbul: A panel data analysis. Sustainable Cities and Society, 65, Article 102619.

Urban, J., & Braun Kohlová, M. (2020). The COVID-19 Crisis Diminishes Neither Pro-Environmental Motivation nor Pro-Environmental Behavior: A Panel Study. PsyArXiv, 9 Nov. 2020. Web. https://doi.org/10.31234/osf.io/k2gmn.

Qu, X., Gao, K. & Li, X. (2020) Impacts of COVID-19 on the Transport Sector and Measures as Well as Recommendations of Policies and Future Research: A Report on SIG-C1 Transport Theory and Modelling (September 8, 2020), Available at SSRN: htp://ssrn.com/abstract=3689209 or https://doi.org/10.2139/ssrn.3689209.

Shokouhyar, S., Shokoohyar, S., Sobhani, A., & Gorizi, A. J. (2021). Shared mobility in post-COVID-era: New challenges and opportunities. Sustainable Cities and Society, 67, Article 102714.

Sun, Q., Feng, T., Kemperman, A., & Spahn, A. (2020). Modal shift implications of e-bike use in the Netherlands: Moving towards sustainability? Transportatiopn Research Part D: Transport and Environment, 78, Article 102020.

Swait, J., Adamowicz, W., Hanemann, M., Diederich, A., Krosnick, J., Layton, D., et al. (2002). Context dependence and aggregation in disaggregate choice analysis. Marketing Letters, 13(3), 195–205.

Tian, X., An, C., Chen, Z., & Tian, Z. (2020). Assessing the impact of COVID-19 pandemic on urban transportation and air quality in Canada. Science of The Total Environment, 144270.

Train, K. (2009). Discrete choice methods with simulation. Cambridge University Press.

Shelat, S., Cats, O. & van Cranenburgh, S. (2020). Avoiding the Crowd: Traveller Behaviour in Public Transport in the Age of COVID-19. arXiv preprint arXiv: 2104.10973.

Usher, K., Jackson, D., Durkin, J., Gyamfi, N., & Bhullar, N. (2020). Pandemic-related behaviours and psychological outcomes: A rapid literature review to explain COVID-19 behaviours. International Journal of Mental Health Nursing, 29(6), 1018–1034.

van den Berg, P., Geurs, K., Vinken, S., & Arentze, T. (2018). Stated choice model of transport modes including solar bike. Journal of Transport and Land Use, 11(1), 901–919.

van Wee, B. & Witlox, F. (2021). COVID-19 and its long-term effects on activity participation and travel behaviour: A multiperspective view. Journal of Transport Geography, 95, Article 103144.

Wu, X., Cao, J., & Huting, J. (2018). Using three-factor theory to identify improvement measures as Well as Recommendations of Policies and Future Research: A Report on SIG-C1 Transport Theory and Modelling (September 8, 2020), Available at SSRN: htp://ssrn.com/abstract=3689209 or https://doi.org/10.2139/ssrn.3689209.

Wu, X., Cao, J., & Huting, J. (2018). Using three-factor theory to identify improvement priorities for express and local bus services: An application of regression with dummy variables in the Twin cities. Transportation Research Part A: Policy and Practice, 113, 184–196.