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Adapting to the new normal: Understanding public transport use and willingness-to-pay for social distancing during a pandemic context

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A B S T R A C T

The COVID-19 pandemic has been a worldwide disruptive event that impacted, to a greater or lesser extent, all countries and economic activities. In the transport sector, stakeholders are still dealing with and learning from its consequences, as many users have changed their preferences towards private and less sustainable modes. In this paper, a mixed logit modelling approach was applied to a vast database from a stated preference survey conducted in Germany to assess the influence of COVID-19 on mobility preferences in three different stages of the pandemic period: lockdown (high-risk of spread, May 2020), post-lockdown (medium risk of spread, June 2020), and a period where the number of infected cases was lower (small risk of spread, October 2020). Several variables were included in the analysis, such as sociodemographic characteristics, mobility habits and preferences regarding future mobility solutions. Three models were developed, one for each pandemic stage. A comprehensive and reflective analysis of the models' results, aligned with other studies' findings, shows that the utility of public transport (PuT) and bicycles, based on individuals' sociodemographic characteristics and choice attributes, compared to cars was affected by the pandemic state. Regarding the influence of crowding inside PuT during the different periods, it was concluded that users are more willing to pay an extra for their monthly passes to have available seats in PuT in the latter stage of the pandemic. The availability of dedicated bike lanes and a shower at the destination were considered attractive factors for cycling during the lockdown phase. Regarding the private car use, the cost of parking is the only attribute that demonstrates a causal effect on the preference for using this mode. This attribute holds a greater relevance during the post-lockdown and "new normal" periods. The results of this study can be helpful to guide policymakers on the definition of actions to counteract the increasing preference for private transport in the future and during disruptions.

1. Introduction

Following the outbreak of COVID-19 in China in January 2020, which quickly escalated into a global pandemic, governments worldwide implemented various measures to control its spread, including social distancing, travel restrictions, and remote work (Ciotti et al., 2020). These actions significantly impacted economic growth and mobility patterns, particularly within the public transport (PuT) sector, due to reduced confidence in crowded spaces (Ferreira et al., 2022; Filgueiras et al., 2023). Learning from the mobility impacts of COVID-19 is essential to emulate scenarios in case of new disruptions, enabling predictions of mobility patterns and preferences that provide transport planners and policymakers with evidence-based tools to adjust services, cope with reduced patronage, and promote safe travels (Gkiotsalitis & Cats, 2021; Guimarães at al., 2023).

PuT modes can be characterized by different attributes, which ultimately are the decision factors, along with the alternative mode attributes, for an individual or group of individuals to select or not PuT as the preferable mode to complete a particular journey. Theoretically, these attributes are almost unlimited and can range from quantitative characteristics such as cost, travel and wait times, and seat availability, among others, to qualitative characteristics such as comfort, image,

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preferences, and mode views. Although capturing the whole range of descriptive attributes that define a specific PuT offer is complex, mode choice is mainly made by assessing a subset of all attributes, which are the key differentiators among the available choices. Travel time and a convenient alignment of departure time and trip purpose are key attributes when long-distance travelers decide to use or not PuT. At the same time, for short trips, commuters decide primarily based on the price and duration of the trip (Rosa, 2021). These insights are further supported by De Vos et al. (2022), who found that travel time is one of the main factors affecting the choice between active modes and PuT, placing travel time as a critical indicator of satisfaction among modes.

With the arrival of COVID-19 and the fear of getting infected, self-imposed social distancing and the implementation of contention measures have significantly altered mobility patterns and preferences during the pandemic (Gkiotsalitis & Cats, 2021; Coppola & Lobo, 2022). In this way, loyalty towards PuT systems has also been challenged. According to Esmalipour et al. (2022), there was an increase in service quality and customer satisfaction with newly placed measures, but still, the perceived attractiveness of using PuT decreased. Nikolaidou et al. (2023), used Moovit data combined with socio-demographics to analyze the impact of COVID-19 on PuT ridership in 87 cities in Europe, showing that ridership decrease is positively correlated with the number of transfers and the average waiting time at stops, but also with the severity of the pandemic in each city. The authors also demonstrated that income inequality is associated with lower PuT abandonment rates, but also improved vehicle disinfection contributes to sustaining ridership. Nevertheless, Ismael et al. (2023) showed that vehicle temperature and cleanliness are not always the main drivers for the intention to use PuT, but rather comfort, low noise, and low crowding. Considering the case study of Budapest, Hungary, the same work also refers that the main operational attributes accounted for by users and non-users of PuT are the frequency, service hour, and proximity. Ulahannan and Birrell (2022) used a discrete choice experiment to quantify the use of PuT together with its most relevant attributes following the lifting of the initial COVID-19 pandemic restrictions in the UK. Fare cost still came as the main driver for ridership, followed by travel time, estimating a value of time of 0.21 GBP/min for private trips or long trips but, but a lower value of 0.09 GBP/min for commuting trips. It was also shown that real-time information is a positive driver of PuT utility.

The reduced use of PuT increased the modal split of private cars (Almlöf et al., 2021). Thombre and Agarwal (2021) showed that captive PuT users were willing to pay more for having/using a private motorized vehicle, but also willing to pay for more resilient PuT. Focusing on longitudinal behavior, Srikanth et al. (2023) analyzed the mobility preferences before, during, and after COVID-19 restrictions in Bangalore North, India. The authors showed an increased use of shared mobility, walking, and private transport during lockdown, but a returning to pre-pandemic levels after the restrictions were lifted. Interestingly, PuT had a huge decrease, from first to last mode during lockdown, but when the restrictions were lifted, it has only recovered two thirds of its pre-COVID-19 mode share. Factors such as travel time savings, comfort, cleanliness, and infection concerns gained relevance from the pre- to the post-pandemic period. In a study conducted among Hungarian university students, Varga et al. (2023) found a shift from public transport to individual vehicles during the pandemic. Focusing on vulnerable social groups, Dadashzadeh et al. (2022) conducted a systematic literature review to analyze changes in travel behavior before, during, and after the pandemic, showing that PuT was the most impacted due to infection concerns. According to the authors, the pandemic has accentuated the problem of inclusivity in transport, particularly affecting the elderly and disabled commuters.

In the meantime, several studies focused on the new trends and risk aversion factors when travelling, precisely the case of in-vehicle crowding, as the risk of infections is likely to increase with the occupancy rate of shared vehicles (Hörcher et al., 2021). The crowding influence has been a widely researched topic on PuT in the past (Li & Hensher, 2011; Kim et al., 2015) that has regained interest with the COVID-19 pandemic. Passengers generally show disutility for crowded vehicles, particularly those with no available seats. Shelat et al. (2022) indicated that onboard crowding and infection rates have been the most important factors for risk perception during the pandemic, while emphasizing the known adverse effects of crowding with risk awareness. Recently, researchers have studied users' willingness to pay (WTP) for social distancing. Rossetti et al. (2022) investigated how customers in New York traded off social distancing measures and increased waiting times during the peak of the pandemic. Using a WTP methodology derived from a conditional logit model, the authors found that customers were willing to wait longer to access a public space with a better social distancing scenario, in this case, a physical store. In a PuT context, Bawambale et al. (2023) analyzed the WTP for COVID-19 mitigation measures in developing countries. This study conducted a stated preference (SP) survey before and during the pandemic, confirming that travel time or cost attributes are less relevant than safety factors. Awad-Núñez et al. (2021) conducted a nationwide survey in Spain during the spring of 2020 to understand how users expected safety measures to be incorporated in PuT. The measures were praised; however, they were unwilling to pay more in the PuT fair to implement them. The estimated values of crowding in the scenario caused by COVID-19 create an opportunity to better forecast users' needs and expectations to not avoid PuT in future disruptions. The insights given by the WTP values may be valuable for policy designs to provide efficient solutions to the expected demand with a predicted return.

The literature yielded different outcomes regarding the factors affecting transport mode choice during the COVID-19 pandemic, underscoring the susceptibility of results to case-specific considerations, including the limitation imposed by the time frame. While, in some studies, conventional service-related attributes retained significance, in other studies, attributes emerging from the pandemic context assumed greater importance. Traditional analyses frequently use cross-sectional data, which offer a limited view of preferences at singular moments, and simplistic models like multinomial logit, which may fail to capture the diversity in preferences among individuals. In this study, the limitation imposed by temporal constraints is addressed by offering a distinct perspective on choice preferences during specific intervals of the pandemic, distinguished by varying degrees of restrictions and viral transmission. Specifically, this research aims to contribute to the existing body of knowledge by (i) investigating the extent to which mobility preferences shifted in response to the unprecedented risk levels posed by the COVID-19 pandemic, particularly focusing on the temporal aspect of this extraordinary global event, and (ii) further explore the impacts on PuT ridership by analyzing the individuals' WTP for increased social distancing onboard PuT. This method considered the diversity of individual preferences, enabling a detailed analysis of the factors affecting mode selection.

The methodology employed involved the development of three mixed logit models utilizing data obtained from a national cross-sectional SP survey conducted at various stages of the pandemic in Germany. The evolution of the impacts of transport mode choice attributes and individuals' sociodemographic factors was analyzed as the pandemic progressed for PuT, cycling, and private car using odds ratios. Additionally, the WTP to ride on PuT under the same attribute conditions was calculated. Besides the understanding of the impacts of an extremely disruptive event on PuT, this study aims to support further comparisons with the current circumstances in the aftermath of the pandemic era. As emerging transport modes, such as e-scooters, ride hailing and car sharing, only account for 1 % of the modal split for commuting in Germany (Anke et al., 2021), these modes are not considered in the analysis.

The remainder paper is structured as follows. Section 2 describes the data and the survey, and Section 3 presents the methodology applied. In Section 4, the main results are presented and discussed. Finally, a brief conclusion and guidelines for future research are provided in Section 5.

2. Data description

The available data for this study was obtained through an online survey in Germany conducted during three different one-week periods (survey waves, SWs). The first survey wave (SW 1) was initiated on the 17th of April 2020, coinciding with the beginning of a national lockdown. After the relief of restrictions, the second survey wave (SW 2) started on the 2nd of June 2020. The third and last time the survey was online (SW 3) was on the 12th of October 2020, during a "new normal" setting – the survey asked for the behavior and preferences considering the conditions observed during the previous week – following fewer COVID-19 cases and fewer viral propagation over the summer period. Hence, the considered periods are of interest due to the different stages of the COVID-19 pandemic evolution and corresponding national sanitary measures to prevent its propagation, which is also aligned with previous studies (Almlöf et al., 2021; Hensher et al., 2021; Marsden & Docherty, 2021).

A panel data provider was used to acquire respondents during the three waves, ensuring that the three datasets are comparable, i.e., each wave represents the same population. The respondents were selected on the basis of a representative quota according to age, gender and place of residence. A total of 1600 validated responses completed per SW were gathered through the online survey platform LimeSurvey. Considering that Germany has a population of approximately 83 million inhabitants, the respondents' data provides a statistical significance corresponding to a 95 % chance that the actual value is within $\pm$ 2.5 % of the measured value (Israel, 1992) ($p = 0.05$), which yields the most conservative results. Despite online surveys becoming a commonly employed method, particularly in the context of the pandemic, it is important to acknowledge the possibility of response bias (Ball, 2019). The data related to the sociodemographic characteristics and mobility habits considered for this study is described in Table 1.

The minimum required age to respond the survey was 18-years old, and the eldest respondent was 82-years old. The respondents with more than 65-years old were not fully covered through the survey, so they were not considered for the analysis. The defined age intervals were based on a similar survey conducted in Switzerland in 2021 (Molloy, 2021). Regarding gender, only male and female categories were considered. Non-binary individuals were not analyzed, as they represented only 0.16 % of the sample. The relative frequency of the age categories in the sample is representative of the German population aged between 18 and 65 years, with the exception of a slight overrepresentation of the group aged 45–55 years (29 % versus 23 %), and a similar underrepresentation of the group aged 55–65 years (18 % versus 24 %). However, when combining both groups, the proportion of respondents aged 45–65 years is exactly the same of the German population (47 %). Gender diverges in only 1 %, as there are 51 % of women in the German population (Eisenmann et al. 2021). The occupation of the respondents was grouped to increase the sample in each category, particularly the not employed group, which includes unemployed, pensioners, housekeepers, and job seekers.

Table 1
Respondents' sociodemographic characteristics and mobility habits.

Variable	Mean	Category	Relative frequency (%)
Age	43	18–25	10
		25–35	21
		35–45	22
		45–55	29
		55–65	18
Gender		Female	52
		Male	48
Education		Basic or secondary	68
		Higher	32
Occupation		Full-time	55
		Part-time	14
		Not employed	22
		Student	9
Income (EUR/month)	2352	0–500	8
		500–1500	13
		1500–3000	55
		3000–5000	19
		> 5000	5
Ownership		Bike	69
		E-bike	14
		Car	81
Ridership		PuT	15
		Cycling	44
		Car	41
Commuting time (min)	23.5		

The SP survey was structured around two groups of questions: (i) the sociodemographic characteristics and mobility habits of the respondents at the time of the survey and (ii) the preference of the respondents when different graphic scenarios and mode choice attributes are presented. The SP experiment was designed according to Hensher et al. (2005), adopting an orthogonal design with four blocks, resulting in 64 cards, i.e., 16 per respondent. The experiment initiated with a set of instructions explaining to the respondents the meaning of each element in the experiment cards. Then, the respondents were provided with the following context (translated from German): "In the following part of the survey, we present you several maps where you have the option to choose between three different transport modes. We would like to find out whether and to what extent your transport mode choice would change under different boundary conditions. It is especially important that you read carefully the information on the card and make a conscious decision. Naturally, the current coronavirus crisis is influencing your mobility behavior. Therefore, please start from your behavior before the pandemic and make your decision on this basis. Please put yourself in the following initial situation: You must decide how you will travel to work, your place of education, or any other regular commute in the long term. You have the choice between private car, public transport, and cycling. Your destination is located directly in the city center and you are on the road at peak times. In the morning, this would be between 8:00 and 9:00 a.m., and in the evening between 5:00 and 6:00 p.m. There are no delays on local public transport, whereas there is a risk of traffic jam on the road. For each picture, please choose the option that is most attractive to you".

Each one of the 16 cards shown to each respondent depicted three options to travel, i.e., by private car, PuT, or cycling, specified with different attributes and attribute levels associated to hypothetical scenarios explicitly created to evaluate the influence of COVID-19 on mode choice. The mode choice attributes include amenities (e.g., bike parking and shower at work) and monetary and non-monetary (e.g., crowdedness) costs. The complete mode choice attributes are presented in Table 2. Afterwards, the multiple experimental scenarios per respondent are considered in the mode choice model by including a panel parameter to account for panel data, i.e., a mixture of logits with panel data is considered (see Section 3).

Fig. 1 illustrates an example of a card. Option A relates to using a car in a scenario that requires a certain parking fee, a certain time to find a parking spot, and a certain walking time to the destination. Option B depicts an individual riding in PuT with a slight busy occupancy level. Option C shows the use of cycling in a flat street without a bike lane and clear weather. Further details on the SP survey design, data collection, and modelling process are described in (AUTHORS' REFERENCE).

3. Methodology

A mixture of logit with panel data modelling approach is chosen as the data has a panel effect, as mentioned in Section 2. This approach allows to capture correlations across repeated choices made by a given individual. In the general mixed logit model, the individual-specific coefficients (or parameters) can be assumed to be random rather than fixed. This allows for heterogeneity among individuals in terms of their preferences and decision-making behavior (McFadden & Train, 2000).

Table 2
Available travel modes, list of the attributes and possible scenarios referred to as levels used in the cards of the survey.

Mode	Attribute	Level 1	Level 2	Level 3	Level 4	Level 5
PuT	Trip duration (% of trip duration by private vehicle)	50	100	200		
	Cost (EUR/month)	30	60	120		
	Number of transfers	0	1	2		
	Headway (min)	5	15	30		
	Walking time to the closest station (min)	5	15	30		
	Occupancy	Not busy	Slightly busy	Busy		
Cycling	Trip duration (min)	10	30	45		
	Bike lane	Yes	No			
	Amenities	Yes	No			
	Terrain	Hill	Flat	–		
Car	Trip duration (min)	15	30	45		
	Cost (EUR/month)	30	60	120		
	Parking scenario (cost (EUR/day), parking time (min), walking time (min))	Parking lot (2, 5, 10)	Street (1, 10, 5)	Street (1.5, 10, 5)	Street (free, 10, 10)	Company (free, 0, 1)
All alternatives	Weather	Rainy	Clear			

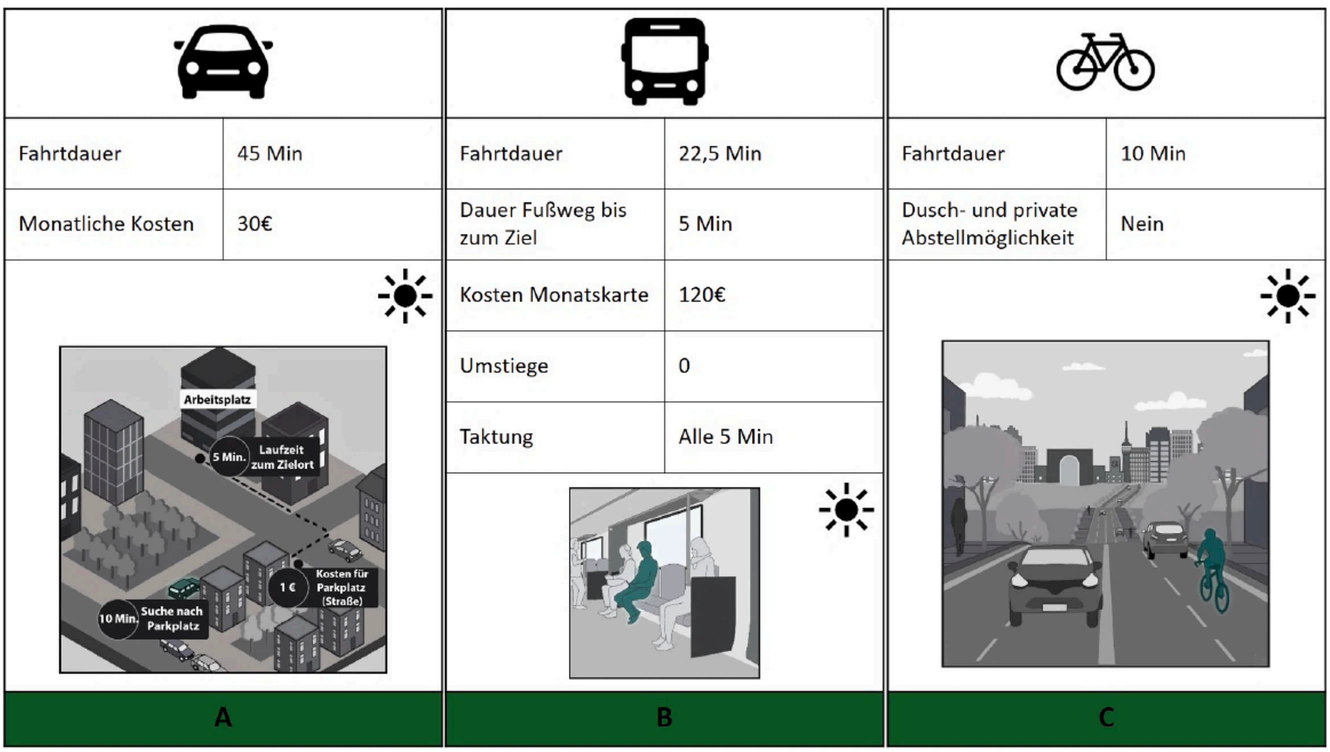

Fig. 1. Example of a graphic card containing a set of scenarios shown to the survey respondents to represent the utility of private car, PuT, and cycling, with different attributes.

The mixed logit model assumes that the utility or satisfaction of an individual derived by each alternative choice is a linear function of a set of attributes or characteristics of that choice and an error term. The error term represents the unobserved factors that influence the decision-making process.

The utility U_{nj} of alternative j for individual n is modelled as:

$$U_{nj} = \beta_{nj}X_{nj} + \varepsilon_{nj} \tag{1}$$

where β_{nj} is a vector of individual-specific coefficients drawn from a distribution f(β), which captures the heterogeneity of preferences among individuals, X_{nj} is a vector of observed attributes or characteristics of alternative j, and ε_{nj} is an independently- and identically-distributed error term with a Gumbel distribution, representing the unobserved factors influencing the decision-making process.

The probability of an individual choosing a particular alternative is obtained by applying the logistic function to the individual-specific utility of that alternative in relation to the utilities of all the other alternatives in the choice set. The logistic function transforms the continuous utility values into probabilities between 0 and 1. The probability P_{nj} that individual n chooses alternative j from a choice set J is given by:

$$P_{nj} = \Pr\left(U_{nj} > U_{ni}, \forall i \in J\right) \tag{2}$$

This probability can be expressed as:

$$P_{nj} = \frac{exp\left(V_{nj}\right)}{\sum_{i \in J} V_{ni}} \tag{3}$$

where V_{nj} is the representative utility of alternative j for individual n, which is the expected value of U_{nj} over the distribution of individual-specific coefficients β_{nj}. This can be expressed as:

$$V_{nj} = E(U_{nj}|\beta_{nj}) = \int_{\beta_{nj}} \beta_{nj} X_{nj} f(\beta_{nj}|\theta) d\beta_{nj} \tag{4}$$

where θ are the parameters of the distribution f(β).

The use of panel data has the underlying assumption that there is serial correlation, as the error terms associated with the observations obtained from the same individual are highly correlated with the unobserved variables (Krueger et al., 2021). Thus, the model is specified to account for sequences of observed choices with intrinsic correlation among the choices of a sequence. For this, the model included distributed alternative-specific constants (σ) with Monte Carlo draws from a normal distribution (Bierlaire, 2018). The Biogeme package for Python was used for model estimations, as this package provides a comprehensive framework for discrete choice modelling, including various model specifications and error distributions (Bierlaire, 2020). The model includes several observed attributes of the alternatives, such as price and travel time. Individual-specific variables, such as age and monthly income, were also included as additional explanatory variables. Several utility functions were tested, and the number of estimation draws was changed as the errors and coefficients converged (reaching 5000 draws as a good compromise between computing time and error). The final utility functions, after removing some statistically insignificant or correlated attributes are depicted below:

$$\begin{aligned} U_{PuT} = {} & ASC_{PuT} + \beta_{AgePuT} Age + \beta_{IncomePuT} Income + \beta_{HighEducPuT} HighEduc + \\ & + \beta_{UsePuT} UsePuT + \beta_{TimePuT} TimePuT + \beta_{CostPuT} CostPuT + \beta_{WalkPuT} WalkPuT + \\ & + \beta_{Transfers} Transfers + \beta_{Headway} Headway + \beta_{Seat} Seat + \sigma_{PuT} \end{aligned} \tag{5}$$

$$\begin{aligned} U_{Cycling} = {} & ASC_{Bike} + \beta_{AgeBike} Age + \beta_{IncomeBike} Income + \beta_{HighEducBike} HighEduc + \\ & + \beta_{CommuteBike} CommuteBike + \beta_{TimeBike} TimeBike + \beta_{BikeLane} BikeLane + \\ & + \beta_{Hill} Hill + \beta_{Shower} Shower + \beta_{WeatherBike} Weather + \sigma_{Bike} \end{aligned} \tag{6}$$

$$\begin{aligned} U_{Car} = {} & \beta_{TimeCar} TimeCar + \beta_{CostCar} CostCar + \beta_{CostPark} CostPark + \\ & + \beta_{TimePark} TimePark + \beta_{WalkPark} WalkPark + \sigma_{Car} \end{aligned} \tag{7}$$

where ASC_{PuT} and ASC_{Bike} are the alternative-specific constants, and σ_{PuT}, σ_{Bike}, and σ_{Car} are the multivariate, normally-distributed alternative-specific constants that capture the intrinsic correlations among the observations of the same individual. The meaning of the variables included in the utility functions is depicted in Table 3. With the exception of the binary variables (y/n), all variables were considered as continuous.

The estimated coefficients within the utility functions of the three considered modes were estimated and subsequently analyzed through the computation of the corresponding odds ratio (OR). The OR represents the factor by which the odds of the outcome of interest increase or decrease for a one-unit increase in the predictor variable of interest. An OR of 1 indicates no association between the predictor variable and the outcome. An OR greater than 1 indicates a positive association, and an OR smaller than 1 indicates a negative association (Train, 2009). From the coefficients of the mixed logit model, the OR was obtained by calculating the exponential of each estimated coefficient β.

Furthermore, to better understand how the mode choice and individual attributes impacted respondents' decisions of using PuT during the three SWs, the WTP for social distancing onboard PuT was analyzed. WTP assessment can be an instrumental tool during project appraisal and to inform future analyses on crowding valuation (Li & Hensher, 2011). A downward trend in the willingness to use PuT has already been depicted in previous studies and surveys worldwide during the pandemic (Gkiotsalitis & Cats, 2021). The present study aims to understand to what extent respondents are willing to pay to ride in PuT, in particular when low levels of vehicle occupancy are considered, as similar to a recent study by Tirachini et al. (2016), but considering also a temporal perspective, ultimately providing planners and PuT operators with information on important variables that attract more customers (Awad-Núñez et al., 2021).

Table 3
Description of the variables in the utility functions.

Mode	Variable in the utility function	Description
PuT	Age	Age of the respondent
	Income	Income of the respondent (hundred EUR/ month)
	HighEduc	Respondent holds a higher education degree (y/n)
	UsePuT	Frequently user of PuT (y/n)
	TimePuT	PuT trip duration (min)
	CostPuT	Cost of using PuT (EUR/month)
	WalkPuT	Walking time to the nearest PuT station (min)
	Transfers	Number of transfers to conclude the PuT trip
	Headway	Headway of the PuT (min)
	Seat	Seat availability (y/n)
Cycling	Age	Age of the respondent
	Income	Income of the respondent (hundred EUR/ month)
	HighEduc	Respondent holds a higher education degree (y/n)
	CommuteBike	Regular commuter by bicycle (y/n)
	TimeBike	Bicycle riding time (min)
	BikeLane	Dedicated bike lane (y/n)
	Hill	Hilly terrain (y/n)
	Shower	Amenities at the destination (y/n)
	Rain	Rainy weather (y/n)
Car	TimeCar	Car trip duration (min)
	CostCar	Cost of running a car (EUR/month)
	CostPark	Cost of parking a car (EUR/day)
	TimePark	Time to find a parking spot and park (min)
	WalkPark	Walking time from vehicle to destination (min)

Considering the data provided by the survey cards, it is possible to calculate the WTP associated with PuT and analyze its variations over the course of the pandemic. In the panel data mixture of logits specification, the estimator of WTP is a simple ratio of coefficients because only the alternative-specific constant is assumed to be distributed across respondents. Therefore, the additional monetary value that the respondents are willing to pay per month to ride in PuT corresponding to a unitary increase of a given sociodemographic characteristic or PuT attribute, associated to coefficient β_j, is represented by:

$$WTP = \frac{\beta_j}{-\beta_{CostPuT}} \tag{8}$$

where the symmetric of $\beta_{CostPuT}$ is considered because an extra cost provides disutility (evidenced by a negative estimated coefficient $\beta_{CostPuT}$). Considering, for example, the variable related to occupancy inside PuT, Fig. 2 represents the three occupancy scenarios shown to respondents: busy, slightly busy and not busy. A value of 1 was attributed to this variable if a respondent's card choice includes either a not busy or a slightly busy vehicle, and 0 if it includes a busy vehicle. This binary classification reflects two states of vehicle occupancy: non-crowded vehicles with available seats and crowded vehicles without available seats. If the WTP increases from wave to wave, then the respondents are willing to pay more for seat availability, and subconsciously for a non-crowded space, implying the urge for social distancing.

4. Results

In this section, the findings about the mobility preferences during distinct phases of the COVID-19 pandemic in Germany are presented. The results allow to explore the nuanced dynamics shaping transport behavior amid fluctuating pandemic conditions and the influence of

Fig. 2. Example of three graphic cards shown to the survey respondents regarding the levels of occupancy in PuT: not busy, slightly busy, and busy.

various factors on mode choice probabilities.

Tables 4–6 show the modelling results for PuT, cycling, and car, respectively. The coefficients (β) of the sociodemographic characteristics, mobility habits, and alternative-specific attributes presented in Tables 4 and 5 for the three collected SWs correspond to the utility of travelling by PuT and bicycle, respectively, in relation to the private car, considered as the reference category. Table 6 shows the estimated coefficients for the alternative-specific attributes of the reference category, the car. From the model calibration, it was found that the agent effect σ, responsible for serial correlation due to panel data, is significant for the three modes, which means that the developed modelling approach is able to capture intrinsic correlations between the observations of the same individual.

Focusing on PuT, the results in Table 4 show that, over the three SWs, the probability of choosing this mode over the private car is positively correlated with the habit of using it and seat availability, and negatively correlated with the respondents' income and some attributes expressing disutility of PuT: TimePuT, CostPuT, and WalkPuT. The number of transfers and the headway also showed a negative correlation with the probability of choosing PuT, but only for the lockdown period, denoting that the interaction with other users at stations have lost relevance over the course of the pandemic. In turn, Table 5 shows that, over the three SWs, the probability of choosing cycling over the private car is negatively correlated with age, trip duration, and inclement weather. As the other variables did not present a steady and significant impact across the three analyzed periods, it is possible to infer that such factors are not consensual among the population when it comes to decide to commute by bicycle. As so, group behavior related to choosing cycling over car can be characterized by a relatively small number of factors when compared to the choice between PuT and car. Regarding the attributes of the private car, considered as reference, Table 6 shows that the trip duration, the running costs, and the inconvenience of finding and paying for a parking spot are significant predictors of the disutility of this mode.

For a better understanding of the evolution of the mobility preferences of the respondents across the three analyzed periods of the pandemic, the results are further debated in terms of OR; Figs. 3 and 4 depict the OR (colored point depending on the wave) for PuT and cycling, respectively, considering the private car as reference for the three SWs, and Fig. 5 represents the odds ratios related to the car attributes. The lines associated with each value represent the confidence interval at 95 %.

The analysis of the forest plot in Fig. 3 reveals notable shifts in preferences for PuT across the considered periods. Being a frequent use of PuT emerged as the strongest motivator for continued use after the outbreak, with an OR of 4.80 in the first wave and 3.30 in the second and third SWs. However, the number of transfers within the PuT system decreased its utility during the first lockdown (OR = 0.78), but became less significant in the subsequent periods. The availability of seats is another prominent attribute of PuT that served as a significant incentive for users, particularly during the early stages of the pandemic (OR = 1.19). However, as the virus spread decreased over time, the importance of traveling in a less crowded space has slightly decreased, although it remains an important characteristic for passenger comfort. Travel and walking times associated with PuT, the cost, and the service frequency did not show any discernible effect on the likelihood of choosing this transport mode.

Individuals with a university degree feel more attracted to use PuT instead of cars, with odds ratios of 1.65 during the post-lockdown period. However, in the "new normal" period (SW 3), this relationship became less relevant, possibly due to the increased likelihood of affluence to PuT services. Regarding age and income groups, no strong relationship with PuT use was observed across the study period.

Table 4
Results of the mixed logit model regarding the probability of choosing PuT, considering the car as reference.

Variable	SW 1		SW 2		SW 3	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ASC_{PuT}	−0.071	0.250	−0.936***	0.211	−0.825***	0.218
σ_{PuT}	0.843***	0.133	−0.912***	0.105	−0.849***	0.090
Age	0.001	0.005	0.001	0.004	0.002	0.004
Income	−0.017***	0.004	−0.018***	0.004	−0.013***	0.003
HighEduc	0.160	0.130	0.506***	0.121	0.083	0.113
UsePuT	1.560***	0.119	1.200***	0.103	1.220***	0.100
TimePuT	−0.030***	0.001	−0.007***	0.001	−0.005***	0.001
CostPuT	−0.016***	0.001	−0.003***	0.001	−0.003***	0.001
WalkPuT	−0.032***	0.002	−0.012***	0.002	−0.005***	0.002
Transfers	−0.245***	0.024	0.028	0.020	−0.008	0.019
Headway	−0.011***	0.002	−0.001	0.002	0.002	0.002
Seat	0.170***	0.042	0.156***	0.040	0.074*	0.038

*** statistically significant at 1 % level;.
* statistically significant at 10 % level.

Table 5
Results of the mixed logit model regarding the probability of choosing cycling, considering the car as reference.

Variable	SW 1		SW 2		SW 3	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ASC_{Bike}	1.840***	0.302	0.902***	0.217	0.897***	0.227
σ_{Bike}	−2.210***	0.091	−1.380***	0.076	−1.330***	0.070
Age	−0.024***	0.006	−0.017***	0.005	−0.014***	0.005
Income	−0.018***	0.005	−0.006	0.004	−0.009**	0.004
HighEduc	0.175	0.171	0.521***	0.125	0.166	0.126
CommuteBike	−0.006	0.004	−0.008***	0.003	−0.004	0.003
TimeBike	−0.090***	0.003	−0.026***	0.002	−0.022***	0.002
BikeLane	0.125***	0.038	−0.093***	0.031	−0.056*	0.032
Hill	−0.021	0.037	−0.003	0.028	0.011	0.029
Shower	0.491***	0.045	−0.050	0.034	−0.019	0.033
Rain	−1.000***	0.054	−0.214***	0.036	−0.286***	0.036

*** statistically significant at 1 % level;.
** statistically significant at 5 % level;.
* statistically significant at 10 % level.

Table 6
Results of the mixed logit model regarding the mode attributes of the car.

Variable	SW 1		SW 2		SW 3	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
σ_{Car}	1.910***	0.0783	−1.650***	0.068	−1.600***	0.070
TimeCar	−0.026***	0.002	−0.008***	0.001	−0.007***	0.001
CostCar	−0.014***	0.001	−0.007***	0.001	−0.006***	0.001
CostPark	−0.109***	0.023	−0.224***	0.022	−0.240***	0.022
TimePark	−0.040***	0.005	−0.049***	0.005	−0.051***	0.005
WalkPark	−0.008	0.008	0.019***	0.006	0.026***	0.007

*** statistically significant at 1 % level.

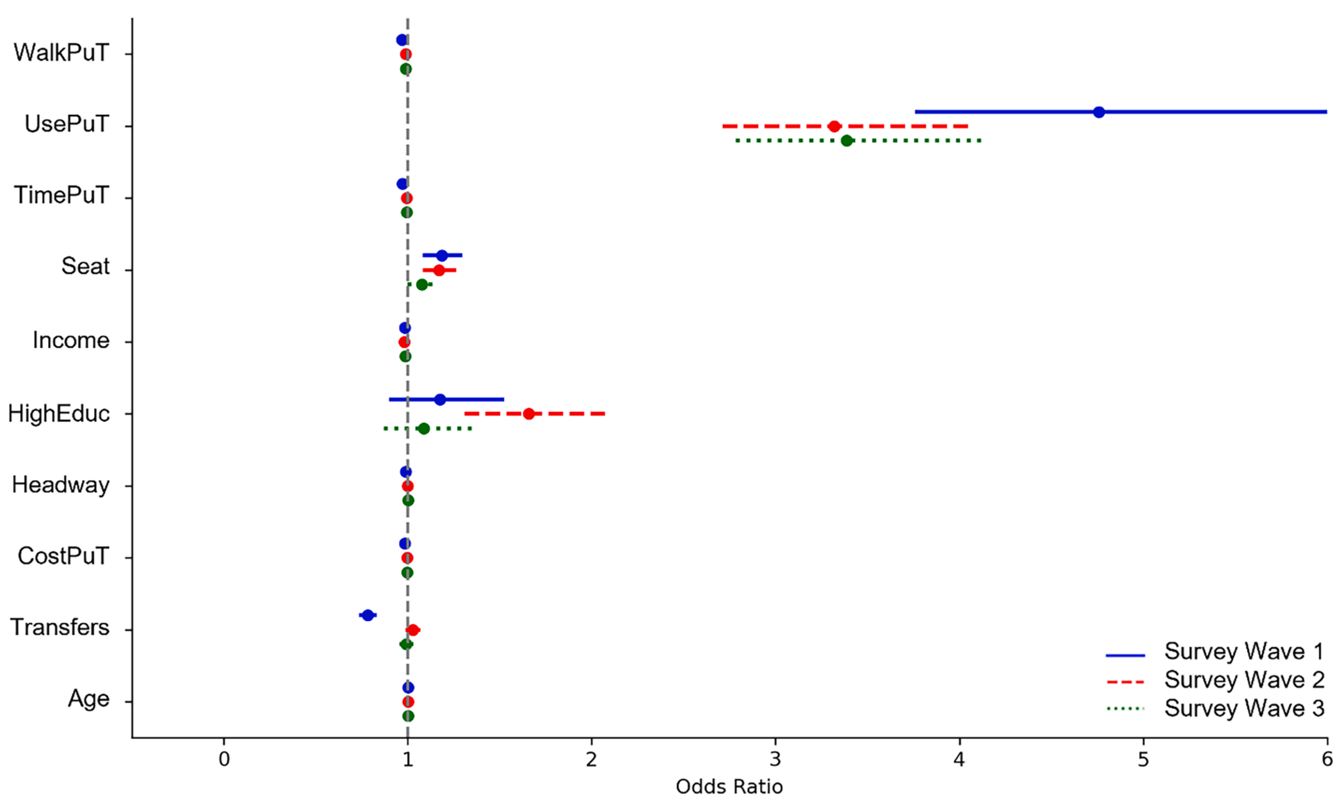

Fig. 3. Odds ratios for PuT, considering the car as reference.

Fig. 4 depicts more pronounced effects of the analyzed variables on the odds of using a bicycle during the lockdown. In this way, inclement weather was found to significantly decrease the odds cycling compared to a car (OR = 0.38), while the availability of a shower at the destination (OR = 1.60) and the availability of a dedicated bike lane (OR = 1.13) were considered attractive factors for cycling. Furthermore, an increase

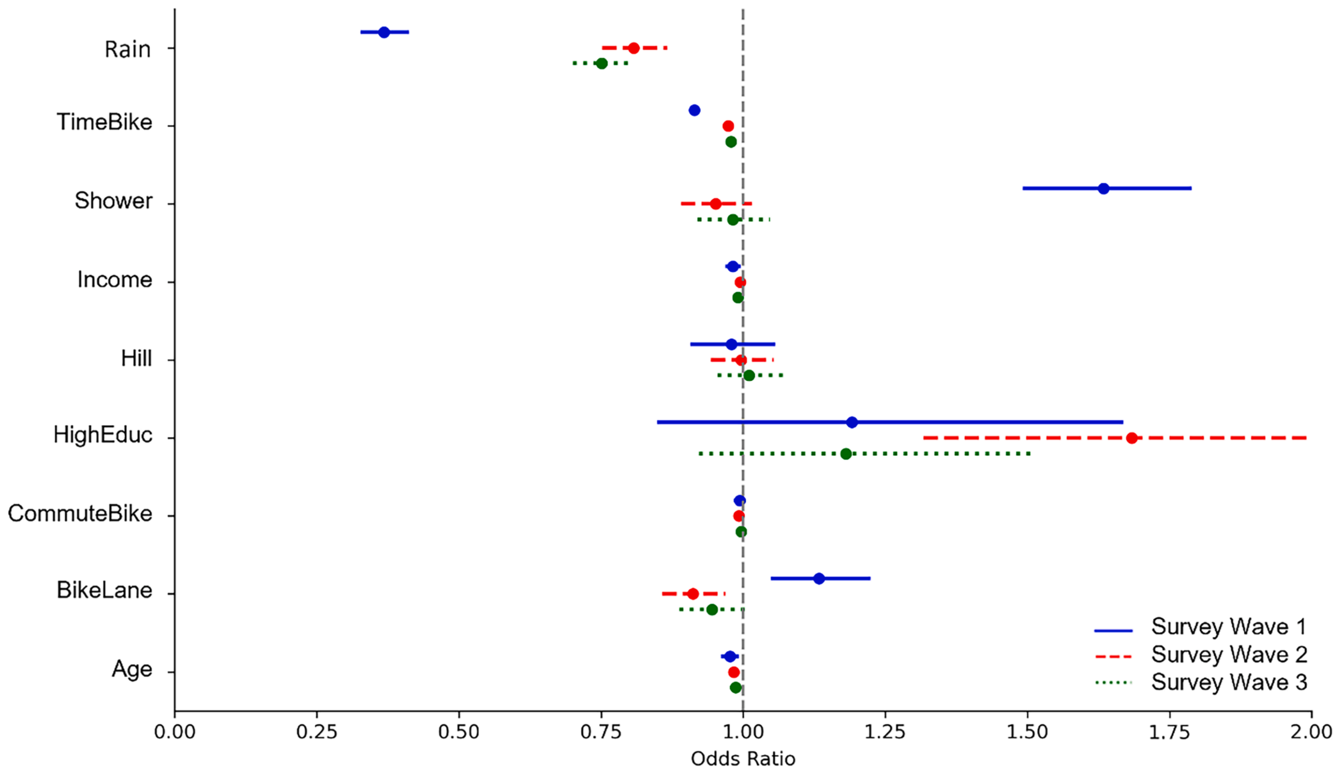

Fig. 4. Odds ratios for cycling, considering the car as reference.

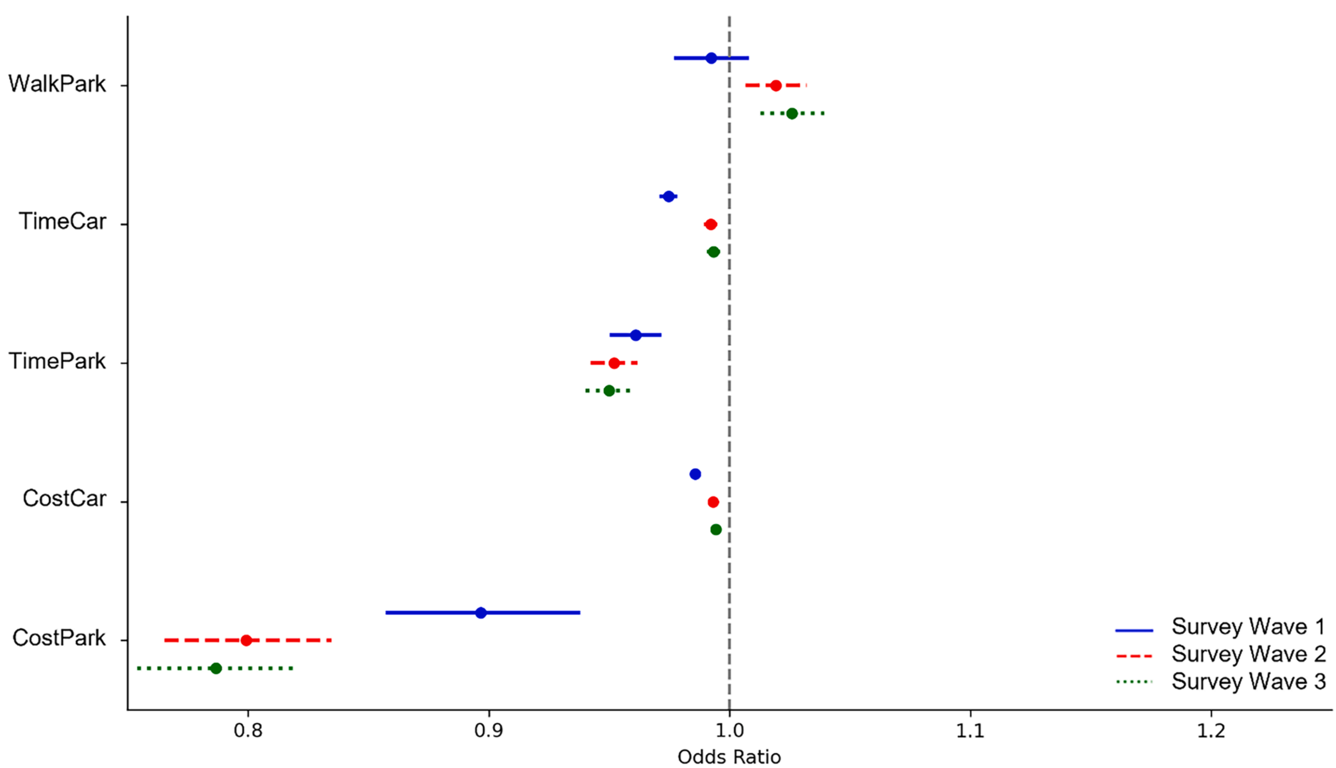

Fig. 5. Odds ratios for car attributes.

in bicycle riding time was associated with slightly reduced odds of choosing this mode during the same period (OR = 0.91), as respondents denoted a preference for using cars in longer trips.

The income level and age of respondents, the total commuting time, and the type of terrain did not exhibit any noteworthy effects on the odds of riding a bicycle. However, individuals with a higher education degree showed to be more prone to choose cycling, especially after the relief of restrictions imposed during the first lockdown period (OR = 1.68), which suggests that higher education attainment may be associated with an increased consciousness towards the use of more sustainable transport modes.

Regarding the private car attributes, from Fig. 5 it is possible to observe that the cost of parking is the only attribute that demonstrates a causal effect on the preference for using this mode ($0.79 \leq OR \leq 0.90$). This attribute holds a greater relevance during the post-lockdown and "new normal" periods (SWs 2 and 3). In contrast, the other examined attributes did not exhibit a significant impact on the odds of choosing a car. This suggests that, throughout the pandemic, individuals were inclined to bear the expenses of owning and running a car, regardless of other factors influencing mode choice.

To better understand the impact of the COVID-19 pandemic on PuT ridership, WTP estimations were obtained based on sociodemographic and PuT characteristics using Eq. (8). The results are shown in Table 7.

The results in Table 7 are naturally in line with the results of the mixed logit model for PuT (Table 4). In this way, the income of individuals emerged as a significant controlling factor influencing their WTP for using PuT. In all SWs, individuals earning a higher income are less prone to choose PuT, but this trend was particularly pronounced during the post-lockdown and "new normal" periods. Variables such as the walking time to the nearest station and the travel time by PuT showed similar trends. While negative WTP values across waves reflect the higher disutility of PuT usually associated with an increasing travel time and with individuals with higher economic statuses, these factors were not so relevant for the respondents during the lockdown, perhaps because the imposed travel restrictions would anyway prevent most trips. When the restrictions have gradually been lifted, but still under the fear of infection, the respondents had actually the chance to opt by other modes, showing even fewer positive attitudes towards PuT. On the other hand, frequent PuT users demonstrated a consistent WTP for using this mode, as it increased as the pandemic evolved and more people naturally started using the system. More transfers per trip and less service frequency (higher headway) are also associated with disutility and a lower WTP, however these effects have been statistically significant only under severe mobility restrictions, reflecting, once again, more perceptions that an actual intention to use.

During the post-lockdown and "new normal" periods, the respondents were driven by other factors, such as the time they had actually to spend on public spaces and the crowdedness of such spaces. In relation to this later point, during the post-lockdown period, users expressed a WTP an additional 55 EUR per month for available seats and a less crowded environment, compared to only 11 EUR and 28 EUR per month during the lockdown and the "new normal" periods, respectively. This suggests that users placed a higher value on social distancing and comfort right after the lockdown, reflecting a cautious behavior when they had to start traveling again at a time of great uncertainty regarding the development and availability of a treatment against the disease and the surge of new variants of the COVID-19 virus.

Table 7
Respondents' WTP (in EUR/month and percent variation between SWs) for riding in PuT, considering a unitary increase of the sociodemographic variables and PuT attributes.

Variable	WTP (EUR/month)			WTP (% variation)		
	SW 1	SW 2	SW 3	SW 1 to SW 2	SW 2 to SW 3	SW 1 to SW 3
Income	−1.10	−6.45	−4.90	486 %	−24 %	345 %
HighEduc	n/a	179.43	n/a	n/a	n/a	n/a
UsePuT	98.73	425.53	463.88	331 %	9 %	370 %
TimePuT	−1.91	−2.48	−2.03	30 %	−18 %	6 %
WalkPuT	−2.03	−4.11	−4.14	103 %	0.75 %	104 %
Transfers	−15.51	n/a	n/a	n/a	n/a	n/a
Headway	−0.70	n/a	n/a	n/a	n/a	n/a
Seat	10.76	55.32	28.14	414 %	−49 %	162 %

Note: n/a – not statistically significant or not applicable.

5. Discussion

In this section, the results of this study are contrasted with the findings from previous research, with the aim of providing insights and long-term implications related to the impacts of disruptive health crises on public transport systems.

In relation to mode choice, as mentioned before, our results indicate that some factors led to the decline of popularity of PuT in favor of alternative modes, such as cars and bicycles, especially during the early stages of the COVID-19 pandemic. Also in Germany, Eisenmann et al. (2021) observed a similar trend, with increasing car use to mitigate the risk of infection. However, relying on private cars leads to additional travel costs. A study conducted by Brough et al. (2021) in North America highlights the significant impact of socioeconomic disparities on mobility habits during the pandemic. The authors found that individuals with lower levels of education and income continued to rely on PuT, even during periods of high risk of virus propagation, and despite the reduction of PuT services. The current study also showed a negative correlation between income and the probability of choosing PuT, but, on the other hand, higher education was associated to a higher preference for PuT. This may be caused by different mobility cultures and safety perceptions towards PuT between North America and Europe. In Switzerland, the survey conducted by Molloy (2021) showed that higher income groups reduced their daily travel more during the first lockdown and immediately after this lockdown, but were less affected in their mobility during the second infection wave and corresponding partial lockdown period. Individuals with a permanent access to a private vehicle have also showed smoother variations of their daily travel distance throughout the different stages of the pandemic.

Prior to the pandemic, studies have examined the significant heterogeneity in crowding perception among commuters, considering variables such as seating arrangement (Kim et al., 2015), trip purpose and distance, and income (Whelan & Crockett, 2009). Cho and Park (2021) demonstrated that the crowding impedance on public transit during the pandemic has been more pronounced compared to pre-pandemic levels. To better understand the role of the pandemic in crowding perception, it is crucial to consider additional factors that focus on individual perceptions. The complexity of the problem arises from the numerous factors that influence crowding, which stem from the subjectivity of social individuals, their diverse attitudes, and past life experiences (Przybylowski et al., 2021). For instance, Echazu and Nocetti (2020) emphasized the significance of vaccine discovery, restricted capacity of healthcare systems, and disease vulnerability as essential factors influencing perceived risk. Accordingly, the present research showed the reducing importance of social distancing across the different analyzed periods. In fact, the interaction with other passengers inside the vehicles, represented by seat availability, and at PuT stops/stations, represented by the number of transfers and headway, became less relevant as the pandemic evolved and risk perception decreased. Aghabayk et al. (2021), Das et al. (2021), and Parker et al. (2021) complemented these factors with sanitation/cleaning policies, use of personal protective equipment (e.g., face masks), and infection rates. Furthermore, Dong et al. (2021) highlighted the role of various sources of information and their credibility in increasing or decreasing uncertainty during a crisis.

Regarding the WTP for social distancing, the obtained results also align with previous research, such as Thombre and Agarwal (2021) and Arunwuttipong et al. (2021), who have shown a strong WTP for non-crowded PuT and reinforced cleaning plans. Other studies, including Sánchez-Cañizares et al. (2020), Awad-Núñez et al. (2021), and Parker et al. (2021), indicated that users desired the implementation of such measures, but expected no additional costs for using PuT services. However, these studies lack the longitudinal analysis of the WTP, which is a unique contribution of the current analysis.

From these findings, it can be inferred that disruptive events may widen equity gaps in transport, as the most economically privileged groups have access to a higher set of alternative modes. In the case of the COVID-19 pandemic, individuals with higher income have often demonstrated to choose private cars over PuT, reinforcing their WTP for an alternative that is perceived to minimize the risk of infection. Besides the environmental concerns towards the use of less sustainable modes, this can also exacerbate concerns regarding an inequitable incidence of the disease among different social classes (Messacar et al., 2020).

Long-term policy implications drawn from the presented findings underscore the need for proactive measures to address evolving transport needs in the context of disruptive events such as public health crises. The WTP for noncrowded PuT and reinforced cleaning plans, as evidenced by different studies, point towards sustained investments in sanitation and crowd management strategies within mass transit systems. However, while users desire such measures, they may not be willing to bear additional costs in the future (Awad-Núñez et al., 2021), especially as the risk perception fades away over time. This underscores the importance of balancing service enhancements with affordability to ensure the attractiveness of PuT for different users (dell'Olio et al., 2011).

The observed decline in the preference for PuT, coupled with an increased reliance on private cars, highlights the need for strategies to keep PuT attractive and accessible, and to promote active modes, for example, as complementary access and egress modes (Rietveld, 2000). Measures aimed at addressing inequities of access to transport, such as reducing fares for low-income individuals and providing PuT services in underserved areas, are essential to mitigate the accessibility gaps exacerbated by disruptive events like the COVID-19 pandemic (Susilo et al., 2021).

Additionally, the complex interplay of factors influencing the utility and safety perceptions of public transport underscores the need for multifaceted approaches to address passenger concerns. As so, policymakers must consider a wide range of variables in devising strategies to restore trust in PuT, including traditional operational factors (e.g., occupancy and service frequency), highly uncertain context-derived factors (e.g., vaccine availability, healthcare capacity, and sanitation policies in a pandemic context), and travel behavior and customer preferences (Tirachini & Cats, 2020). As so, enhancing communication strategies and ensuring transparency in information dissemination are crucial for fostering public confidence and reducing uncertainty during crises (Dong et al., 2021).

In summary, long-term policy responses and transport planning efforts must attend to safety, equity, and sustainability considerations. By addressing the diverse needs and concerns of commuters, policymakers can contribute to more resilient transport systems in face of future challenges and disruptions.

6. Closing remarks

The COVID-19 pandemic has shifted many aspects of daily life. Mobility is one of those aspects that changed the most, initially by an almost complete stop of daily trips, and after by changing patterns and preferences that have emerged and continue to challenge the transport sector. This paper contributes to the body of knowledge about how those patterns and preferences evolved during the pandemic by using panel data and models that enable comparisons across distinct stages of the disruptive event. A mixed logit methodology was implemented to analyze data from an SP survey considering three transport modes: PuT, cycling, and private car. This approach accounted for the heterogeneity of individual preferences and allowed for a more nuanced examination of the factors influencing mode choice. Previous studies often rely on cross-sectional data, which only provides a snapshot of preferences at specific points in time, and on simpler models (e.g., multinomial logit), which may overlook the variation in preferences across individuals.

The findings of this study highlight the relevance of choice attributes compared to sociodemographic characteristics in mode preference. The analysis revealed specific attributes that significantly influence mode choice, such as seat availability and the number of transfers for PuT, weather conditions for cycling, and the cost of parking for the private car. Additionally, this work analyzed the attributes that affect the most the WTP to ride in PuT, with a special focus on seat availability due to the call for social distancing during the pandemic. The results showed that individuals were more willing to pay for a low-occupancy PuT service with empty seats once people had to start traveling again after the first lockdown was lifted than in relation to the lockdown period. The WTP is significantly higher immediately after the lockdown, when the fear of infection and the uncertainties regarding a treatment for the disease were still quite high. The WTP decreases as the "new normal" takes over, during which the population starts to get used to oscillations of the infection rates and consequent adjustments of mitigation measures by the governments, and to perceive the availability of a treatment in the short term.

The main limitation of this study is that it relies on an SP survey, which may introduce sampling bias, as the respondents' statements may not fully align with their actual behavior. Also, this research did not consider respondents with more than 65-years old, as this age group of the population was not fully covered by the sample. While this study investigated the mobility preferences across three distinct stages of the COVID-19 pandemic, the analysis may not have captured the full spectrum of changes in mobility behavior over time. Factors such as evolving public health guidelines and restrictions, vaccination rates and socioeconomic conditions, could influence mobility preferences beyond the surveyed time periods, limiting the findings to a context before the end of the pandemic was declared. Moreover, considering different mobility habits and cultures, different stages of development of the transport networks, and different ways the pandemic unfolded from one region to another, e.g., depending on the local infection rates and containing measures, the extrapolation of the results, particularly outside Europe, should be carefully considered.

The authors highlight the need for further research to validate and expand upon these findings, particularly in different temporal and spatial contexts. These recommendations acknowledge the evolving nature of travel behavior and emphasize the importance of ongoing research to understand impacts and trends in PuT ridership and to inform decision-making in transport planning and policy in a post-pandemic world.

Availability of data and material

Data availability is restricted. Any enquiries should be addressed to the corresponding author.

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CRediT authorship contribution statement

Manuel Filgueiras: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Marco Amorim:** Writing – original draft, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **António Lobo:** Writing – review & editing, Funding acquisition, Formal analysis. **António Couto:** Software, Methodology, Conceptualization. **Mira Kern:** Methodology, Data curation. **Sara Ferreira:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

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.

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