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Travel behavior before and after COVID-19. A hybrid choice model applied to a panel dataset

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ABSTRACT

After two decades of psychological research into travel behavior, one would anticipate a thorough understanding of the cognitive processes guiding travel choices. However, the intricate and unpredictable nature of mobility dynamics often obstructs efforts to promote sustainable travel behaviors. While hybrid choice models (HCMs) incorporating latent variables prove invaluable in analyzing travel behavior, there remains a critical need for further exploration into effectively managing these variables. Typically assessed at singular time points, these variables pose challenges in analyzing individual characteristics based on their fluctuations. Moreover, deriving actionable policy implications from HCMs is challenging due to the inherent nature of psycho-attitudinal variables, which exhibit limited responsiveness to alterations in alternatives. Only a significant disruptive event could induce notable shifts in individuals' psycho-attitudinal characteristics. The objective of this paper is to investigate two aspects: i) to study if and how norms, intentions and perceived behavioral control change after a strong shock such as the pandemic, and ii) to analyze the differences in the HCMs results estimated by using data collected before and after the shock. The study involves a panel dataset gathered during a VTBC Program which involved three phases, two of which before and straight after the first lockdown. Our results show that norms were less impacted by COVID-19 and lost importance post-lockdown. There was a notable decline in the intention to use sustainable modes and an increase in car usage, with significant differences in perceived behavioral control between those who maintain and those who change their transport modes.

Introduction and literature review

One of the most felt interests of the transport scientific community, among others, is to identify an effective way of achieving a massive car-use reduction.

Especially, two important fields were studied more in-depth: on one hand the study of psycho-attitudinal aspects which drive behaviors, and, simultaneously, the development of econometric models able to take into consideration the aforementioned qualitative aspects, with the aim to make it possible to accurately forecast travel demand to define the best policies implications.

One approach is that of incorporating behavioral theories in discrete choice models by means of hybrid choice model (HCM), which theoretically allows the analyst to benefit from the economic and behavioral foundations of both approaches (Bouscasse, 2018).

In the literature, there are numerous studies which employ latent variables to analyze travel behavior by means of hybrid choice models. Among of the most recent ones are: Etzioni et al. (2021) in the context of automated vehicles; Parady et al. (2021) with a review of validation practices; Huan et al. (2022) in the context of electric vehicle adoption; Piras et al. (2021) in the context of cycling; Thorhauge et al. (2019) in the context of departure time choice; Sottile et al. (2019a,b) in the context of cycling perception; Soto et al. (2018) in the context of parking choice; Sottile et al. (2017) analyzing the switch from car driver to more sustainable modes; Glerum et al. (2014) in the context of a travel mode choice; Prato et al. (2012) for a route choice analysis.

The integration of latent variables in the utility function helps to improve our understanding of travel choice and to adapt public policies, but the richness of structural equation models still needs to be explored to fully embody the psychological theories explaining mode choice (Pronello and Gaborieau, 2018).

Hybrid choice models which include latent variables are very useful when analyzing travel behavior (Walker, 2001). However, the handling of latent variables in utility functions still needs to be explored.

There are several criticisms linked to psycho-attitudinal factors and HCMs. One of the many critiques is that latent variables are measured

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through a discrete scale of indicators (Likert) at a certain point in time, making it impossible to analyze intra-personal characteristics based on variations in the latent construct itself (Chorus and Kroesen, 2014). Longitudinal data could be a solution, since it allows to observe variations in psycho-attitudinal factors depending on external factors. Another criticism is that HCMs do not allow the derivation of policy implications or policy evaluations, as psycho-attitudinal variables are intrinsic characteristics and are thus not sensitive to variations in the alternatives (Chorus and Kroesen, 2014). Nevertheless, though psycho-attitudinal variables have been used to define policies through factor analysis (Mokhtarian, 1998; Li & Zhang, 2023), the same cannot be said of hybrid discrete choice models (Yáñez et al., 2010).

Few studies estimate HCMs using data collected before and after an event could be considered a shock. Yáñez et al. (2010) estimate a hybrid model in a short-survey panel context for data among many alternatives. Sottile et al. (2019a,b) estimate a hybrid choice model jointly by using a two-wave panel dataset to evaluate, on one hand, the long-term effects on travel mode choice of the implementation of a new light rail line, and, on the other, to detect any changes in the psycho-attitudinal factors and socio-economic characteristics. There are other studies that use panel data which is although collected through a stated preference survey. Jensen et al. (2013) estimate a hybrid choice model using jointly the stated choices before and after the test period of three months in using electric vehicle.

One of the greatest challenges is finding how to change psycho-attitudinal factors to trigger sustainable behavior, considering that many individuals reconsider their habitual travel behavior only following radical changes in the context of choice (a so-called shock effect). Only a shock effect could trigger a shift in people's psycho-attitudinal characteristics (Yáñez et al., 2009). The global outbreak of COVID-19 can definitely be considered such a strong shock effect. The spread of COVID-19 and the government responses to address the outbreak have deeply modified population's behavior, also determining important modifications to the environment of urban areas and to the transportation system. The containment measures, such as working/studying from home, and the economic downturn have determined not only a considerable reduction in daily travel, which could be "a blessing in disguise" (Muhammad et al., 2020), but a strong discrimination against public transport and shared mobility. Anyway, how much has this event changed the psycho-attitudinal factors? Several studies were developed in the last three years in correlation with the COVID-19 pandemic that can definitely be considered a strong shock effect and a precious opportunity to measure effects before and after such shock. Few studies have been published on behaviors of users in the phase before and after the lockdown and, also in this case, often using stated preference data. Scorrano and Danielis (2021) gathered choice-related and attitudinal data to analyze the means of transport used before and during the Corona-virus pandemic of 2020 using an ICLV model. Aaditya and Rahul (2021) estimated an integrated choice and latent variable (ICLV) framework which was adapted to understand the impact of the novel behavioral constructs, such as awareness of the disease and people's perception of the strictness of lockdown towards the mode choice in the post pandemic scenario. Chen et al. (2022) estimated a HCM using stated preference data to examine the influence of latent aspects on individuals' travel choices due to policies related to COVID-19.

In light of the above, this paper aims to analyze if and how the travel behavior of a sample of public employees and university students changed after COVID-19. We carried out a two steps survey that allowed us to collect longitudinal data, before and after a strong shock such as COVID–19. Then we estimated two different HCMs using respectively the data collected before and after the lockdown to be able to identify and disentangle any change in psycho-attitudinal aspects. The contribution is twofold: first, we want to analyze if and how norms, intentions, and perceived behavioral control, change following a strong shock such as the COVID-19 pandemic, and second, we try to identify the potential differences in the HCMs results estimated by using data collected before and after the shock.

The contribution addresses three issues:

1. availability of longitudinal psycho-attitudinal data, which enables the analysis of intrapersonal characteristics based on variations in latent constructs, thereby allowing policy implications to be drawn from the estimation of HCMs;
2. evaluation of the shock effect, such as the COVID-19 pandemic, on individuals' psycho-attitudinal characteristics;
3. combination of the previous two points: estimation of hybrid models with longitudinal data collected before and after a shock. This contribution highlights the opportunity to observe significant changes in psycho-attitudinal variables over time.

The study is based on the data gathered during the Voluntary Travel Behavior Change Program (VTBC) named "Svolta Cagliari". The aim of the program was promoting a more sustainable travel behavior among individuals working and studying within 7 districts of the municipality of Cagliari, the main city in Sardinia (Italy). The program involved different steps, two of them conducted before and after the first COVID-19 lockdown restriction imposed by the central government in Italy. The surveys allowed us to gather participants' socio-economic and psycho-attitudinal data at two points in time.

The remainder of this paper is structured as follows: Section 2 we illustrate the methodology used, shows the characteristics of the sample and describes the modelling approach. In Section 3 we present the results obtained from the model estimation and conduct an analysis of the effects of every latent variable. We provide conclusions in Section 4.

Methodology

Study context

The present research is based on a dataset collected within the framework of a Voluntary Travel Behaviour Change Program (VTBC) named "Svolta Cagliari", which was financed by the Italian government through the Ministry of the Environment. The program aimed to spread awareness about more sustainable travel practices among workers and students regularly commuting into the municipality of Cagliari, the regional capital of Sardinia (Italy). Cagliari is the largest city of Sardinia, covering an area of 84.58 km^2 with its municipality and counting around 149,092 residents (Italian Statistic Institute – Istat, 2023). The mobility demand in the city of Cagliari is derived by the needs of 67,514 individuals who commute daily. Of these, 32 % travel for study purposes, and 68 % commute to reach their workplace. Around 59 % of them use motorized vehicles for their travels, 25 % use active mobility (walking or biking), and only 16 % use public transport (Italian Statistic Institute – Istat, 2011).

The VTBC program entailed three stages, although, for the purposes of this study, we only used the data collected during the following two stages (Fig. 1.):

1. From November 2019 to January 2020: approximately 48,000 individuals were contacted to complete a web survey about their usual travel behavior. The questionnaire allowed to collect information on the respondents' home to work/study trips, on their intentions, perceived behavioral control and social norms toward the use of sustainable means of transport, and on their socio-demographic profile. By the end of the stage, 5,006 fully compiled questionnaires were collected.
2. From October 2020 to December 2020: all the individuals that completed the first questionnaire were contacted again to fill in a second on-line survey, to describe their travel behavior during the different phases of the COVID-19 pandemic, leading to 1,900 (38 %) questionnaires being compiled fully. This second step of the program was not scheduled at first, but we deemed it was necessary once the

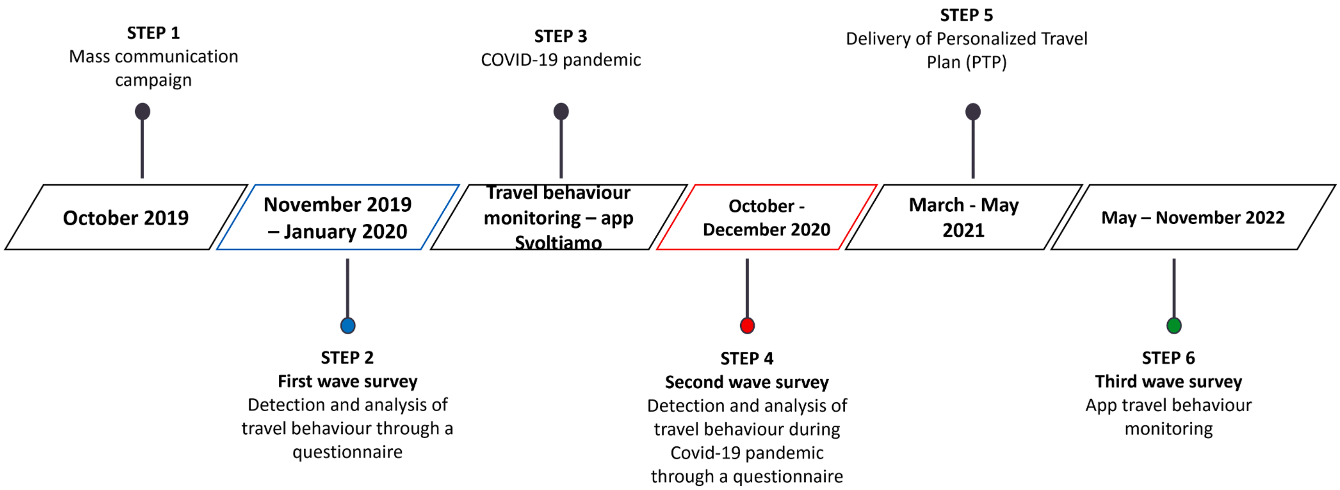

Fig. 1. Program phases.

virus began spreading. Compared to the original survey, we added some questions about travel behavior and remote work/study options, while maintaining all other questions to enable direct comparisons; this is especially important for the questions investigating psycho-social elements.

Between October and December 2020, the Italian government imposed a series of restrictions to limit the risk of COVID-19 transmission. Specifically, the Italian territory was divided into zones based on the epidemiological risk determined by the number of cases and the incidence of the virus. The risk zones generally included the colors yellow (moderate risk), orange (medium risk), and red (high risk). High-risk areas faced more stringent restrictions. Cagliari was classified as a yellow zone, indicating moderate risk. Therefore, the existing restrictions included: remote learning for all levels of schools, early closure (6 pm) of non-essential activities, limitations on travel between provinces, restrictions on restaurant services (maximum of 4 diners per table), and encouragement of remote work options wherever possible. Additionally, to reduce the risk of COVID-19 transmission, there were limitations on the use of public transportation, with capacity restrictions and recommendations for maintaining social distancing and wearing masks while traveling. These measures became stricter in anticipation of the Christmas holidays.

Compared to 2019, 2020 saw a series of changes in travel behavior due to the pandemic and government-imposed restrictions. According to the report by ISFORT (2021), weekday mobility volumes decreased by 22.3 % compared to 2019 in terms of trips and by 39.8 % in terms of distances covered (passenger*km). The weekday mobility rate dropped to 69 %, partially compensated by the increase in local mobility (very short walking trips). The average number of trips per person also significantly decreased (from 2.1 to 1.7), as did the average time per person spent on mobility (from 50 to 33 min) and the average distance per person traveled each day (from 24 to 15 km).

Traffic trends for passenger transport in 2020, analyzed by the Technical Mission Structure of the Ministry of Infrastructure and Sustainable Mobility (Mims, 2021), confirm the negative dynamics described, with significant variability throughout the year. During the first lockdown period, traffic flows decreased by up to 80 %, then gradually increased from May to August, fully recovering (or even surpassing) the pre-Covid levels at the beginning of the year, before decreasing again from the end of summer until the end of the year. The reasons for travel in 2020 showed a significant increase in the proportion of family management (from 26.2 % in 2019 to 34.3 %), in contrast with the collapse of school mobility (from 4.6 % to 1.7 %) and a marked reduction in leisure mobility (from 37.2 % to 33.9 %). The share of work-related mobility remained relatively stable, but with a significant reduction in absolute values.

2020 was a year of a deep crisis in public transport, due to social distancing rules and the fear of contagion, which saw its modal share halved (from 10.8 % to 5.4 %) and losing over 50 % of passengers during the year. At the same time, the share of intermodal trips (from 6.5 % to 1.7 % of motorized trips) collapsed. On the other hand, soft mobility saw strong growth, particularly thanks to walking trips, whose share increased from 20.8 % in 2019 to 29 % in 2020, and the consolidation of bicycle and micromobility (from 3.3 % to 3.8 %). The car maintained its dominant position in the choice of Italians, reducing its modal share by only 2.5 points (from 62.5 % to 59 %).

Sample characteristics

The dataset used in the present study was obtained from the first and second surveys. The sample used includes of all the 1,632 individuals that answered and filled in completely both questionnaires. Although the initial sample collected with the first questionnaire was representative of workers/students in the service sector, constituting 86.5 % of the total active population in Cagliari, the final sample, which coincides with users who completed both the PRE and POST questionnaires, does not maintain the same representativeness. This is due to the fact that only a specific category of users has a propensity to participate in panel surveys (this aspect is being analyzed in a work in progress). Therefore, the descriptive statistics for the endogenous variables of interest in this document cannot be generalized to the population of the city of Cagliari. However, when estimating individual causal relationships from a sample based on exogenous sampling, the unweighted approach is the most efficient estimation technique (providing more precise parameter estimates than a weighted approach). Therefore, in our model estimates, we use the unweighted approach (Solon et al., 2015).

Table 1. summarizes the distributions of the socio-demographic characteristics of the sample. The results show that the majority of individuals live in Cagliari and most are women. The average age is slightly less than 39 years old. As expected, the sample is relatively educated, has a medium income between € 1,000 and € 2,000, and the average number of household members is about three. 93 % of the respondents has a driver license, 82 % owns a car and 52 % owns a bicycle.

As revealed by the respondents, the most commonly used mode for commuting (51.0 %), before lockdown, is represented by private motorized vehicles (cars and motorcycles), followed by public transport (37.3 %), walking (8.4 %), and cycling (3.3 %). Note that this modal

Table 1
Socio-economic characteristics.

	N	%	Avg		N	%	Avg
Residence location				Education			
Cagliari	960	58.82 %	–	Up to middle school	33	2.02 %	–
Metropolitan City	500	30.64 %	–	High school	674	41.30 %	–
South Sardinia	163	9.99 %	–	Technical/training certificate	26	1.59 %	–
Elsewhere	9	0.55 %	–	Bachelor/master's degree	616	37.75 %	–
Age			38.49	PhD	283	17.34 %	–
from 18 y.o. to 30 y.o.	611	37.44 %	–	Household			
from 31 y.o. to 40 y.o.	246	15.07 %	–	Household members	–	–	3.04
from 41 y.o. to 60 y.o.	697	42.71 %	–	Children in the household	–	–	0.50
over 60 y.o.	78	4.78 %	–	Children up to 10 y.o.	–	–	0.19
Gender				Owns a driving license	1,514	92.77 %	
Female	877	53.74 %	–	Owns a bicycle	852	52.21 %	
Male	755	46.26 %	–	Own a car	1,338	81.99 %	
Occupational status				Cars in the household	–	–	1.71
Employee	845	51.78 %	–	Income (monthly)	–	–	
Student	555	34.01 %	–	from 0 € to 500 €	435	26.65 %	–
Employer	110	6.74 %	–	from 501 € to 1,000 €	150	9.19 %	–
PhD student	74	4.53 %	–	from 1,001 € to 1,500 €	376	23.04 %	–
Unemployed	18	1.10 %	–	from 1,501 € to 2,000 €	379	23.22 %	–
Retired	14	0.86 %	–	from 2,001 € to 3,000 €	182	11.15 %	–
Student/worker	9	0.55 %	–	over 3,000 €	110	6.74 %	–
Homemaker	7	0.43 %	–				

distribution differs slightly from Istat (Italian Statistic Institute) data due to a relevant presence of students in the sample, which represent one of the largest share of public transport users. Chart 1 shows how the modal share changed following the heavy lockdown enforced by the Italian Government in March 2020. Between October and December 2020, 43 % of the sample has chosen or was forced to switch either to work from home or to remote learning. The percentage of workers/students from home in the modal split refers to the portion of people who work or study remotely. During the period of the pandemic, there has been a significant increase in remote work and online learning due to safety measures and lockdowns. Consequently, more people have worked or studied from home instead of commuting to the office or school. This behavioral change is reflected in the diagram to highlight how the modal split has shifted considering the new travel option of staying put.

Among the 57 % who continued to commute, two clusters of individuals could be identified: almost 6 % of the sample changed their means of transport to travel to their workplace/university, with 51 % of those changing in favor of car as driver because private vehicles were preferred to sharing and public mobility, due to the fear of being infected; the other 51 % chose instead to use the same mode they used before the pandemic. Thus, for modelling purposes, we split the dataset in three sub-samples: individuals working/studying remotely (701 individuals), people who kept using the same mode (mode-constants, 837 individuals), and mode-shifters (94 individuals). Each individual has of all three choice options available.

Chart 2 shows the modal split for the total sample and for each identified cluster, before and after the COVID-19 pandemic. Public transport systems have been the most negatively affected, since the largest percentage decrease observed is the one for public transport use after the lockdown (from 37.25 % to 20.07 % for mode-constants and to 2.13 % for mode-shifters) in line with findings from other studies (Falchetta & Noussan, 2020). Most mode-shifters leave the public transport mode by their own choice, and active mobility was the second most popular choice (after car as driver) when the distance allowed it.

The effect of COVID-19 is also easily verifiable from the analysis of travel time, distance traveled, costs, and CO_2 emitted. Specifically, there was an average weekly decrease per person in travel time of 16 h, an increase in travel cost of 1.02 euros, a decrease in distance traveled of 3.95 km, and an increase in CO_2 emitted of 2.49 kg due to the increase in the use of private motorized means of transport.

Latent variables analysis

Concerning psychosocial attributes, we used a psychological

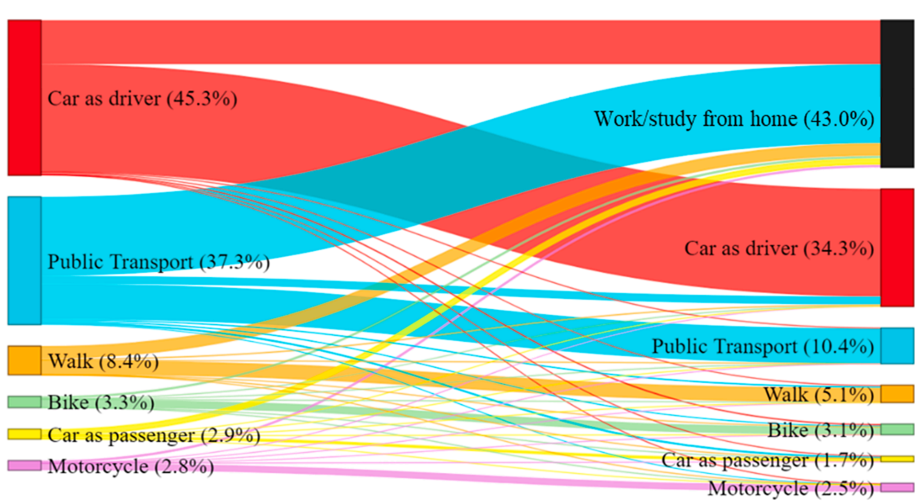

Chart 1. Modal share before and after lockdown.

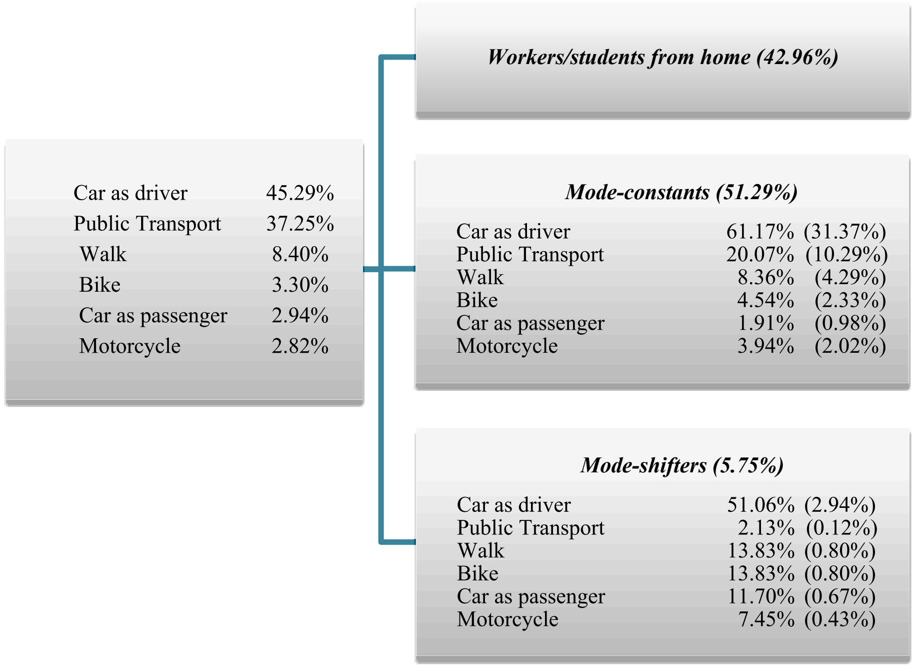

Chart 2. Modal split.

validated scale to define the items for each latent variable to analyze. In collaboration with a team of psychologists, we identified seven latent dimensions with at least three items for each one. Each of the items required the respondent to choose among a 5-points Likert scale (1 = strongly disagree, 2 = somewhat disagree, 3 = neither agree nor disagree, 4 = somewhat agree, 5 = strongly agree) (Likert, 1932). For a detailed description of the latent dimensions, please refer to Giubergia et al., 2024.

In this study we focus on three latent variables:

social norms and moral norms linked to the use of sustainable transport alternatives (Kaiser and Rice, 1974a,b) and measured through the following items:

- Social Norm 1 (SN1): "Most people I know think I should use sustainable transport modes instead of a private car";
- Social Norm 2 (SN2): "Most people I know use sustainable transport modes instead of a private car";
- Moral Norm 1 (MN1): "I feel a moral obligation to use sustainable transport modes regardless of what everybody else does".

Social norms inform people about the behavioral standards that are adequate within their reference group (Bamberg et al., 2011). Moral norms represent our learned expectations regarding the treatment of other individuals in interaction settings (Van Liere and Dunlap,1978).

1. Intentions to use sustainable transport modes/not use their car in the following days (Manca and Fornara, 2019) and measured through the following items:
- Intention 1 (INT1): "During the next two weeks I intend to use sustainable transport modes instead of the car (alone)";
- Intention 2 (INT2): "During the next two weeks I intend to use a private car";
- Intention 3 (INT3): "I am interested in using sustainable transport modes during the next two weeks".
2. Perceived Behavioral Control (PBC) concerning sustainable transport modes (Bamberg et al., 2007) and measured through the following items:
- Perceived Behavioral Control 1 (PBC1): "It would be easy for me to use sustainable transport modes";
- Perceived Behavioral Control 2 (PBC2): "I am certain I can use sustainable transport modes during the next week";
- Perceived Behavioral Control 3 (PBC3): "Using sustainable transport modes is impossible for me".

For PBC, where items are positioned both positively and negatively with respect to sustainable mobility, the values have been recoded consistently to facilitate interpretation.

Even if the results are not reported in this paper, for completeness we performed a confirmatory factor analysis that has confirmed the latent constructs identified ex-ante. The factor loadings were estimated using principal axis factoring with varimax rotation. To measure the sample adequacy of the different constructs, we used the Kaiser-Meyer-Olkin test (KMO), with values of KMO between 0.5 and 1.0 indicating that the sampling is adequate (Kaiser and Rice, 1974a,b).

For each of the three latent variables, we analyzed the values of the indicators before and after the lockdown for each item and then compared them. The differences were calculated between mode-constants and mode-shifters, while students/workers from home were omitted since, in the model, they are going to be the reference alternative and also, during the lockdown, they essentially were not travelers, which are the targets of policy implications defined by mobility planning.

Statistical tests performed on the differences revealed some interesting results. Even if in general social norms play an important role in shaping people's behavior during and after a lockdown (Bavel et al., 2020), in the present study the norms linked to the use of sustainable transport alternatives seem to be the variables less affected by the shock of COVID-19 (Table 2). However, it must be pointed out that, since before COVID-19, our sample does not appear to have a distinct norm. There are statistically significant differences between before and after the lockdown just for the items SN1 (*t*-test = -3.167) and SN3 (*t*-test = -3.045) of the mode-constants, while all the others did not register any significant change. Specifically, it seems that norms lose importance after the lockdown. This is in line with the expectative that, in the face of a health-related worldwide emergency, we do not care as much about what others think about the modes of transport we use.

Conversely, there are significant shifts in the intentions (Table 3). For both sub-samples there is a significant decrease in the intention to use

Table 2
Norms differences before and after lockdown.

NORMS	Mode-constants (837)				Mode-shifters (94)			
Statement	Before	After	Δ (Aft-Bef)	*t*-test	Before	After	Δ (Aft-Bef)	*t*-test
SN1	2.52	2.38	−0.14	−3.167	2.54	2.43	+0.17	1.269
SN2	2.03	2.03	–	–	2.52	2.21	−0.11	−1.010
MN1	3.63	3.49	−0.13	−3.045	3.61	3.81	+0.21	1.626

Table 3
Intentions differences before and after lockdown.

INTENTIONS	Mode-constants (837)				Mode-shifters (94)			
Statement	Before	After	Δ (Aft-Bef)	*t*-test	Before	After	Δ (Aft-Bef)	*t*-test
INT1	3.06	2.86	−0.20	−4.484	4.21	3.00	−1.21	−6.226
INT2	3.67	3.75	+0.08	2.034	2.77	3.68	+0.91	5.271
INT3	2.07	2.34	+0.28	5.591	1.52	2.12	+0.60	3.993

sustainable modes (INT1, *t*-test = -4.484 for Mode-constants and *t*-test = -6.226 for Mode-shifters; INT3, *t*-test = 5.591 for Mode-constants and *t*-test = 3.993 for Mode-shifters) and a corresponding increase of that of using the car (INT2, *t*-test = 2.034 for Mode-constants and *t*-test = 5.271 for Mode-shifters). These differences are more significant for whoever decides to change means of transport in line with the behavior of the same group.

As regards the PBC (Table 4), there are again some significant changes for mode-constants and even more so for mode-shifters. It is interesting to notice that, after the lockdown, all individuals in both groups show large differences in these indicators, since they were less certain they would use public transport in the following week (PBC2, *t*-test = -4.440 for Mode-constants and *t*-test = -5.598 for Mode-shifters) and found it harder to use it altogether (PBC3, *t*-test = 2.530 for Mode-constants and *t*-test = 3.060 for Mode-shifters). The differences are more marked and also more significant for those who decided to change mode.

Modelling framework

A trinomial logit hybrid choice model (Vij and Walker, 2016) is estimated to measure the relationships linking the choices (study/work from home, which is taken as the reference category, keep the same mode, or change mode) to the observed attributes (alternative's level of service, household and individual variables) and the latent constructs. While level of service and socio–demographic characteristics were measured directly, the same does not apply for psycho-attitudinal factors, which were only observed indirectly through indicators. Indicators usually use psychometric scales to try quantifying factors connected to beliefs and traits of decision makers.

The model is defined as follow. Let U_{qj} be the utility associated to alternative j by individual q:

$$U_{qj} = ASC_j + \boldsymbol{\beta}_j \boldsymbol{SE_q} + \theta_j DIST_{\boldsymbol{q}} + \sum\nolimits_n \left(\lambda_{jn} \left(C_n + \boldsymbol{\alpha}_n \boldsymbol{SE}_{\boldsymbol{q}}^{'} + \omega_{qn} \right) \right) + \varepsilon_{qj} \quad (1)$$

where $\boldsymbol{SE_q}$ is a vector of socio-demographic attributes with the corresponding vector of coefficients $\boldsymbol{\beta}_j$, $DIST_q$ is the distance from the origin to the destination and θ_j is the associated coefficient. ASC_j is the alternative-specific constant, $\left(C_n + \alpha_{\boldsymbol{n}} \mathbf{SE}_{\boldsymbol{q}}^{'} + \omega_{qn} \right)$ represents the n-th latent variable (with n = 1, 2, 3), specified as a combination of socio-economic characteristics ($\boldsymbol{SE'_q}$, which can be a different subset from the ones included in the discrete choice) using the associated coefficients $\boldsymbol{\alpha_n}$. C_n is a latent-variable-specific constant while ω_{qn} is a normal distributed error term with zero mean and standard deviation $\sigma_{\omega n}$. λ_{jn} is a parameter associated with each latent variable. Since the kernel of our model is a logit model, ε_{qj} is the error term identically and independently distributed with a Type 1 extreme value distribution.

The statements previously reported in Section 3.3 are used as indicators of the latent variables and the following measurement equations hold:

$$I_{qnk}^{*} = \gamma_k + \zeta_k LV_{qn} + \upsilon_{qk} \quad k = 1, \ldots, K \quad (2)$$

where I_{qnk}^{*} is the k-th indicator for the n-th latent variable, γ_k is the constant, ζ_k is the coefficient associated with the *n-th* latent variable, and υ_{qk} is the normal distributed error term with zero mean and standard deviation $\sigma_{\upsilon k}$. Using the same approach as Ben-Akiva et al. (2002), for identification purposes we set of $\gamma_k = 0$ and $\zeta_k = 1$ for the first indicator of each latent construct ($k = 1$).

The distributions of the latent variables and of the indicators are respectively:

$$f_{LV}\left(LV_{qn} | SE_q^{'}; \alpha, \sigma_\omega \right) = \frac{1}{\sigma_\omega} \phi \left(\frac{LV_{qn} - \left(C_n + \alpha_n SE_q^{'} \right)}{\sigma_\omega} \right) \quad (3)$$

Table 4
PBC differences before and after lockdown.

PBC	Mode-constants (837)				Mode-shifters (94)			
Statement	Before	After	Δ (Aft-Bef)	*t*-test	Before	After	Δ (Aft-Bef)	*t*-test
PBC1	2.81	2.78	−0.03	−0.726	3.96	3.67	−0.29	−1.751
PBC2	2.96	2.74	−0.22	−4.440	4.28	3.07	−1.20	−5.598
PBC3	2.55	2.68	+0.13	2.530	1.53	2.03	+0.50	3.060

$$f_I(I_q|LV_q;\gamma,\zeta,\sigma_\upsilon) = \frac{1}{\sigma_{\upsilon_k}}\phi\left(\frac{I^*_{qnk} - \gamma_k - \zeta_k LV_{qn}}{\sigma_{\upsilon_k}}\right) \quad (4)$$

Indicators are expressed as a five-point numerical scale, while the error terms are normally distributed. It follows that the measurement equations of the indicators I_{qnk} are expressed by means of an ordered probit model:

$$P(I_{qnk} = 1) = \Phi\left(\eta_1 - I^*_{qnk}\right)$$

$$P(1 < I_{qnk} < 5) = \Phi\left(\eta_I - I^*_{qnk}\right) - \Phi\left(\eta_{I-1} - I^*_{qnk}\right) \quad (5)$$

$$P(I_{qnk} = 5) = 1 - \Phi\left(\eta_4 - I^*_{qnk}\right)$$

where η_i are thresholds defined respectively as $\eta_1 = 0$; $\eta_2 = \eta_1 + \delta_1$; $\eta_3 = \eta_2 + \delta_2$; $\eta_4 = \eta_3 + \delta_3$.

The conditional likelihood can be then written as:

$$P_{qj} = \int_\omega P_{qj}(LV_{qn}(\omega_q))f_{LV_{qn}}(\omega_q)f_{I_{qnk}}(LV_{qn}(\omega_q))f(\omega)\,d\omega \quad (6)$$

Different model specifications were tested by using the software PythonBiogeme (Bierlaire and Fetiarison, 2009). To evaluate the importance of the psycho-attitudinal constructs in the description of choice behavior, and to analyze the trade-off between travel distance and each of the considered latent variables, we computed some direct elasticities (DE) and marginal rates of substitution (MRS), following the same methodology used by Piras et al. (2021).

Results

Table 5 shows the results obtained from the models. There are no differences regarding the signs of the latent variables representing the norms, the intentions, and the perceived behavioral control, neither when comparing mode-constants to mode-shifters, nor when comparing between different observation periods (PRE *vs* POST). There are however differences for the weights and statistical significances of these variables.

The negative sign associated with the norm latent variable, that is opinions and support from other people on the use of sustainable mobility, means that, when the value of this variable increases, the probability that a given individual would choose to travel decreases; this holds true both in the pre- and in the post-lockdown data. When people experience a dissonance between attitudes specific to a mode and the choice of using the same mode, it is more likely for them to adjust their attitudes rather than their behavior (Kroesen et al., 2017).

Before the spread of the virus, the norm latent variable weighs more (1.73 *vs* 0.57) for the mode–shifters. It should be noted that most of the remote workers are students, the modal share of those who still travel is unbalanced towards private motorized vehicles, and that most of those who do change mode, shift from public transport to car as driver.

Although it is not possible to directly compare the coefficients of the pre-lockdown model with those of the post-lockdown model, it can be reasonably observed how the norm latent variable, which is highly significant and is also the most significant latent variable of the pre model, does not present the same level of significance in the post model. This aspect could be correlated to the presence of unobserved effects which emerged due to the pandemic, which is also confirmed by the increased significance of the alternative specific constants in the post model. As a result of a shock effect like the spread of COVID-19, what others think about our behavior produces fewer effects on our choices since the top priority, in these specific circumstances, was that of prioritizing the preservation of our own well-being.

Regarding the intention latent variable, the negative sign, like it happened for the norm one, reveals how, when the intention of traveling by using a car increases, there is still a lower probability of starting a

Table 5
Model results.

Name	PRE		POST	
	Value	Robust t-test	Value	Robust t-test
Discrete Part				
Mode-constant				
Costant	−0.688	−0.680	5.620	3.000
Age	0.036	5.870	0.029	4.790
Male	0.478	3.520	0.404	3.360
Level of education (from 1 to 5)	0.204	3.780	–	–
Car owner	0.342	0.950	–	–
# of car in the household	–	–	−0.063	−0.510
Bicycle owner	0.252	1.500	–	–
Income (from 1 to 6)	0.119	2.560	0.102	2.240
Distance O/D	−1.150	−2.520	−0.458	−1.050
Norm	−0.575	−2.410	−0.153	−0.600
Intention	−0.605	−1.440	−5.000	−3.470
Perceived Behavioral Control	0.786	3.320	5.150	3.730
Mode-shifter				
Costant	0.330	0.180	4.870	1.690
Male	0.511	1.890	0.294	1.240
Driving license	–	–	0.541	0.820
Level of education (from 1 to 5)	0.305	2.560	–	–
Car owner	0.838	1.220	–	–
# of car in the household	–	–	−0.265	−1.250
Bicycle owner	0.848	2.420	–	–
Income (from 1 to 6)	0.211	2.160	0.135	1.330
Distance O/D	−1.930	−1.990	−1.270	−1.290
Norm	−1.730	−3.760	−0.341	−1.000
Intention	−1.390	−1.900	−5.060	−2.560
Perceived Behavioral Control	0.766	1.890	5.160	2.720
Latent variable: Norm				
Mean	2.040	7.270	3.010	13.350
Home-Cagliari	0.381	2.700	0.529	5.260
Age	0.007	1.130	–	–
Level of education (from 1 to 5)	–	–	−0.284	−5.920
Student	0.598	3.560	–	–
# of car in the household	–	–	−0.366	−5.220
Bicycle owner	0.182	1.560	–	–
Latent variable: Intention				
Mean	−0.252	−1.510	1.790	20.790
Home-Cagliari	−0.424	−5.010	−0.574	−7.770
Age 18–30	−0.295	−3.020	–	–
Male	0.125	2.170	–	–
# of household components	−0.129	−2.860	–	–
# of children in the household	0.221	3.620	–	–
Car owner	0.926	5.320	–	–
# of car in the household	0.243	3.390	–	–
Latent variable: Perceived Behavioral Control				
Mean	−1.610	−8.530	0.160	1.880
Home-Cagliari	−0.539	−7.990	−0.536	−8.390
Employee	0.620	7.940	0.144	3.900
Level of education (from 1 to 5)	–	–	0.028	1.920
# of children in the household	0.185	4.120	0.028	1.770
Drive license	0.401	1.840	–	–
Car owner	1.140	7.480	0.130	2.880
Bicycle owner	−0.147	−2.280	–	–
Indicators of latent variables				
Latent variable: Norm				
zetaSN1	0.301	15.940	1.450	22.160
delta1SN1	0.843	19.640	2.120	25.450
delta2SN1	1.460	25.160	0.332	13.360
zetaSN2	0.246	12.300	1.580	27.640
delta1SN2	1.400	25.990	1.230	17.970
delta2SN2	0.898	17.520	0.650	26.170
delta1MN1	0.912	11.750	0.380	12.510
delta2MN1	1.350	20.330	0.842	20.480
Latent variable: Intention				
delta1INT1	0.973	19.410	1.110	21.020
delta2INT1	0.889	15.850	0.981	20.030
zetaINT2	2.010	6.950	2.050	16.870
delta1INT2	0.871	12.380	1.080	12.370
delta2INT2	1.260	19.880	1.370	16.650
zetaINT3	−0.065	−0.360	0.578	12.690
delta1INT3	1.730	20.090	0.876	17.310
delta2INT3	0.827	8.920	1.590	23.280

(*continued on next page*)

Table 5 (*continued*)

Name	PRE		POST	
	Value	Robust *t*-test	Value	Robust *t*-test
Latent variable: Perceived Behavioral Control				
delta1PBC1	0.574	16.130	0.624	18.310
delta2PBC1	1.090	19.770	0.958	19.770
zetaPBC2	4.020	8.230	3.930	9.200
delta1PBC2	1.330	8.480	1.470	9.280
delta2PBC2	1.980	8.780	1.630	9.810
zetaPBC3	2.730	12.060	1.910	14.120
delta1PBC3	1.640	13.310	1.400	16.900
delta2PBC3	2.150	12.940	1.560	15.620
Number of estimated parameters	65		54	
Sample size	1,632		1,632	
Init log-likelihood	−21,577.92		–22,973.798	
Final log-likelihood	−17,594.829		−18,839.877	
Likelihood ratio test for the init. model	7,966.183		8,267.841	
ρ^2 for the init. model	0.185		0.180	
Adjusted ρ^2 for the init. model	0.182		0.178	

trip, more evidently so for mode-shifters. As a matter of fact, the fear of infection of COVID-19 among people has greatly reduced their intention to travel (Aaditya and Rahul, 2021).

In the pre model, the intention latent variable is not highly significant, while it is instead in the post-lockdown model, probably because, after COVID-19 hit, a private car is considered to be the safest means of transport since it allows to avoid coming into contact with other people, thus reducing the risk of being infected. The sign is however still negative, because the individuals would have still preferred to not travel at all.

Perceived behavioral control (PBC), that is the perceived ease of frequently using a car, is the only latent variable which presents a positive sign, both between alternatives and between pre and post waves. The higher the PBC is, the higher is the probability of traveling for everyone. It should be noted in particular how, in the post model, the PBC latent variable shows very high weights and significance, a result which is in line with our expectations.

More generally, it can be observed how the model specifications are different between pre and post, both for the discrete modeling part, but even more so for the latent one. This confirms the fact that COVID-19 produced a change in the psycho-attitudinal disposition of the sample. It is noticeable how the probability of traveling is greater, disregarding the choice of changing mode or not, for males, adults, people with higher education and those with higher incomes. The same probability decreases instead when the distance increases, with a more marked effect in the pre-lockdown model for the mode-constants. In the post model even the distance from the origin to the workplace/university loses its effectiveness in influencing the choice of traveling or not. The distance proved to be also highly significant in the structural equation of the latent variables, in particular the fact of living in the city of Cagliari (represented by the *Home-Cagliari* variable), thus having to cover shorter distances to reach the workplace or the university. It should be noted that those living in Cagliari show lower intentions of using a car and lower perceived behavioral control for car use, while the norm is higher, meaning they are more mindful of what others think about their travel behavior. The fact of living in Cagliari and the shorter distances probably allowed these individuals to use their bike or to walk when traveling, which are effectively favored means of transport, after the car, compared to public transport, after the pandemic (+16.2 % in walking trips was registered in Italy in 2020, according to ISFORT *18° Rapporto sulla mobilità degli italiani*).

Socio-economic variables that influence psycho-attitudinal variables play an important role but with modified effects in the post-pandemic period, likely due to changes in social context and individual priorities. In particular, it can be observed that factors such as employment status rather than student status, car ownership, and residence in Cagliari are the most significant socio-economic variables.

Pre-pandemic, social norms were strongly influenced by residence and student status. The geographical location where a person lives can determine their travel habits and social perceptions. For example, those living in densely populated urban areas might have better access to public transportation and, therefore, stronger social norms regarding public transport use compared to those living in suburbs with fewer transport options. Social norms among students might emphasize the use of public transportation or bicycles, whereas for workers, norms might favor the use of private cars.

The pandemic has forced many people to rethink their travel habits and social priorities. For instance, social distancing and travel restrictions might have reduced the importance of pre-existing social norms related to specific modes of transport. People had to adapt their habits based on new restrictions and emerging norms during the pandemic.

Education level and the number of cars in the household negatively influence social norms because the pandemic affected job opportunities, remote education, and transport needs. For example, many students had to switch to online learning, reducing their need to travel to university and thus impacting transport-related norms. Similarly, the pandemic might have influenced the number of cars a household owns due to changes in income and spending habits.

Numerous socio-economic variables significantly influenced intentions positively and negatively (residence in the municipality, young age, household composition, and car ownership and availability) before the pandemic. However, post-pandemic, the only socio-economic variable found significant is residence in the municipality of Cagliari, which negatively influences the intention to use sustainable modes of transport. This may be because those living outside the municipality, especially students, if they have no other modal alternatives, are forced to use public transport.

Regarding perceived behavioral control, the situation is more stable with the set of socio-economic factors that influence it both pre- and post-pandemic. There are slight differences in significance, but the signs are consistent across the waves.

When analyzing the goodness of fit for both models, the pre-lockdown one seems better than the post model, it has more parameters (65 *vs* 54) due to a higher number of significant variables, which confirms that, after the lockdown, with the same sample and the same socio-economic characteristics, there are without any doubt some unobserved effects inevitably connected to COVID-19.

In order to give scientific evidence to the previous hypotheses and to allow for a direct comparison at a level of each variable of the pre and post models, both direct elasticities (Vij & Walker, 2016) and marginal rate of substitutions (MRSs) were estimated. It should be evident right away that there are some differences for both indicators in the pre and post models. While in the pre model, the travel demand is elastic towards the norm, in the post one it is instead elastic towards the intention (Table 6). MRSs were estimated for the latent variables with respect to travel distance. Like for the elasticities, there are some noticeable

Table 6
Direct elasticity (DE) of latent variables.

Direct elasticity	Pre		Post	
	Mode-constant	Mode-shifter	Mode-constant	Mode-shifter
NORM	−1.475	−4.672	−0.210	−0.561
INTENTION	−0.192	−0.469	−5.740	−6.755
PBC	−0.296	0.674	0.169	−0.007
NORM_DIST	−2.958	−5.221	−0.654	−2.094
INTENTION_DIST	−0.366	−0.653	−0.548	−1.699
PBC_DIST	0.434	0.753	−0.016	−0.026

differences between the two models, further reinforcing what claimed before. In particular, considering the indicators for the intention, an answer differing by one point in the scale given for each indicator, causes, in the post scenario, a willingness to travel longer distances, by 10.92 km, 22.38 km, 6.31 km for mode-constants and by 3.98 km, 8.17 km, 2.30 km for mode–shifters. Regarding PBC instead, it seems the effect is the opposite, with answers differing by one point for each indicator leading to the willingness to travel shorter distances (Table 7).

Conclusions

Numerous transportation research works have explored the factors influencing travel behavior. Especially, two research strands have been carried out in the last two decades: on one hand, from a psychological point of view, researchers try to explore the mechanisms underpinning the travel behavior to be able to trigger sustainable mobility effectively acting on individual motivational levers; on the other hand, there has been an important development of modeling techniques. Hybrid choice models that integrate latent variables in the utility function help to improve our understanding of travel behavior but the handling of latent variables in the utility functions still needs to be explored due to the complexity of the mobility phenomenon. Furthermore, future research must be aimed at providing answers to the doubts raised on the usability of hybrid models in demand forecasting. Two important criticisms are linked to HCMs, the impossibility to analyze intra-personal characteristics based on variations in the latent aspect itself, and the impossibility to derivation of policy implications or policy evaluations, as psycho-attitudinal variables are intrinsic characteristics and are thus not sensitive to variations in the alternatives, could be solved by using longitudinal data.

The strength of this paper is the availability of psycho-attitudinal longitudinal data collected before and after the lockdown. Thanks to this data, we can highlight some important evidence. First, we had the chance to measure differences in norms, intentions, and PBC between two different points in time before and after a shock as COVID-19. Our analysis shows that each latent variable has a different response to the same event. Our sample does not appear to have a distinct norm linked to the use of sustainable transport alternatives. Norms seem to be the variables less affected by the shock of COVID-19 and it seems that norms lose importance after the lockdown. This is in line with the expectative, in the face of a health-related worldwide emergency, people tend to not care about what others think. On the contrary, there are significant differences in the intentions. After the lockdown there is a significant decrease in the intention to use sustainable modes and a corresponding increase in using the car. The fear of contagion on shared vehicles makes the car even more attractive for all potential users, also for public transport users.

As regards the PBC, there are again some significant differences for mode-constants and even more for mode-shifters.

The data available allowed us to specify and estimate a hybrid choice model for measuring the relationships that link the three choices (work/study from home, which is taken as reference category, keep the same mode, shift mode) with individuals' socioeconomic variables, level of service characteristics and the latent factors. When the 'before' and 'after' data are compared one can derive conclusions much more credible than those derived from cross-sectional data (Chorus and Kroesen, 2014). The model results highlight different effect of the three latent variables specified. When the value of the norm increases, the probability that a given individuals would choose to travel decreases both in the pre- and in the post-lockdown data.

Regarding the intention, when the intention of traveling by using a car increases, there is still a lower probability of starting a trip. This result is in accordance with those found in other works; Aaditya and Rahul (2021) found that the fear of infection of COVID-19 among people has greatly reduced their intention to travel.

The higher the PBC is, that is the perceived ease of frequently using a car, the higher is the probability of traveling for everyone.

It can be observed how the model specifications are different between pre and post, both for the discrete modeling part, but even more so for the latent one. This confirms the fact that COVID-19 produced a change in the psycho-attitudinal profile of the sample that cannot be overlooked. The recent Covid-19 pandemic is having serious repercussions on the transport sector and mobility. Consequently, we shall be continuing to collect data over time to understand whether the post covid effect will fade over time or not.

Measuring latent variables at only one point in time and considering psycho-attitudinal factors rather stable, thus assuming they barely change over time, could bring to obtain very inconsistent results.

Based on the significant finding emerging from the analysis, which indicates that each psychosocial variable (norm, intention, and PBC) responds differently to the same triggering event, such as the COVID-19 shock or interventions aimed at changing travel behavior, it becomes crucial to adopt mobility policies that take into account this diversity of responses. This necessitates a targeted and adaptable approach that considers individuals' specific psychological reactions to extraordinary events, whether it be a global pandemic or Travel Demand Management (TDM) initiatives. For instance, while fears related to safety and hygiene may arise during a pandemic, influencing mobility choices, considerations of convenience and established habits may prevail during a TDM program. In both cases, it is essential to understand how social norms, individual intentions, and perceived behavioral control are influenced and adapt mobility policies accordingly. This may involve implementing

Table 7
MRSs of the latent variables for the distance.

	Marginal rate of substitution				
Latent variable	Indicator (recoded)	PRE		POST	
		Mode-constant	Mode-shifter	Mode-constant	Mode-shifter
NORM	SN1 – Most people I know think I should use sustainable transport modes instead of a private car.	0.15	0.27	0.48	0.39
	SN2 – Most people I know use sustainable transport modes instead of a private car.	0.12	0.22	0.53	0.42
	MN1 – I feel a moral obligation to use sustainable transport modes regardless of what everybody else does.	0.50	0.90	0.33	0.27
INTENTION	INT1 – During the next two weeks I do not intend to use sustainable transport modes instead of the car (alone).	0.53	0.72	10.92	3.98
	INT2 – During the next two weeks I intend to use a private car.	1.06	1.45	22.38	8.17
	INT 3 – I am not interested in using sustainable transport modes during the next two weeks.	−0.03	−0.05	6.31	2.30
PBC	PBC1 – It would not be easy for me to use sustainable transport modes.	−0.68	−0.44	−11.24	−4.06
	PBC2 – I am not certain I can use sustainable transport modes during the next week.	−2.75	−1.60	−44.19	−15.97
	PBC3 – Using sustainable transport modes is impossible for me.	−1.87	−1.08	−21.48	−7.76

personalized awareness campaigns, creating specific incentives, and investing in infrastructure that promotes sustainable travel behaviors adaptable to the changing needs and perceptions of individuals. Developing targeted and personalized strategies that encourage sustainable mobility behaviors, taking into account individuals' specific personalities, preferences, and perceptions, is essential. This personalized approach allows for the adaptation of mobility policies to the psychological and behavioral characteristics of each individual, facilitating greater engagement and adherence to initiatives aimed at promoting sustainability in transportation. In this way, the creation of a mobility environment that reflects people's needs and inclinations is fostered, thus contributing to promoting positive and lasting changes in travel habits.

Finally, some limitations that affect our study will be addressed in future research. First, the sample cannot be considered representative of its reference population, but constructing such a panel survey is much more expensive than collecting a simple cross-sectional dataset, in terms of both money and time, thus some simplification is needed. In the panel survey there exists also the risk to miss participants among the different steps. Choosing a convenience sample reduces this risk and allows us to obtain a more robust sample size. However, even if the object of the paper is not to define policy implications, it is not possible to plan properly taking as reference data those collected during the COVID-19 pandemic, our results could be used by mobility managers to define such measures as home/work-study travel plans jointly to communication campaigns to influence travel behavior towards sustainable choices.

Second, from a methodological standpoint, a more complex specification will be employed to explore in-depth the phenomenon. The next step will be the estimation of a hybrid choice model in the context of mode choice including the level of service attributes in the utility function to be able to test artificial scenarios to forecasting demand. Also, a joint estimation could be useful to process panel data, and/or HCM accounts for the serial correlation between error terms in the discrete and latent perceptions, to allow for agent-common unknown factors.

Third, all psycho-attitudinal variables measured shall be analyzed (emotions, attitudes, past behavior, *etc.*) and specified in the model.

CRediT authorship contribution statement

Eleonora Sottile: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Giovanni Tuveri:** Writing – original draft, Formal analysis, Data curation. **Francesco Piras:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Italo Meloni:** Writing – original draft, Project administration, Funding acquisition.

Author contribution

The authors confirm contribution to the paper as follows: study conception and design: eleonora sottile; data collection: giovanni tuveri and francesco piras; analysis and interpretation of results: eleonora sottile and giovanni tuveri; draft manuscript preparation: eleonora sottile, giovanni tuveri, francesco piras and italo meloni. all authors reviewed the results and approved the final version of the manuscript.

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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Data availability

The data that has been used is confidential.

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