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How public transport users would react to different pandemic alert scenarios in the post-vaccine era? An analysis of preferences and attitudes of the users in the metropolitan area of Naples (Italy)

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ABSTRACT

The dramatic experience due to COVID-19 spread has reshaped travel preferences of public transport (PT) users worldwide, especially in urban areas. As the PT is expected to recover its major role in such areas, it is important to understand the factors influencing PT users' willingness to pay (WTP) for onboard safety measures, in the event of future pandemic scenarios. Furthermore, both individual latent traits (e.g. concern for the pandemic, trust/distrust in city services and national government actions) and perceived entity of the pandemic are expected to influence preferences for PT users under such a post-pandemic scenario. This paper analyses the preferences and attitudes of PT users in the Naples metropolitan area (Italy) through a hybrid choice model (HCM). First, WTPs for onboard service features are assessed in three hypothetical pandemic alert scenarios, which are explicitly introduced in the model as context variables. Second, the model allows for assessing the relative importance of onboard characteristics as the pandemic scenario evolves. Third, the model incorporates psycho-attitudinal variables and shows how they impact WTPs. Finally, several policy implications for policymakers and transport companies operating in the study area are derived. In particular: (a) WTPs for increased/reduced occupancy rate and green pass check at the entrance significantly depend upon the latent traits investigated; (b) relative importance of safety measures varies significantly between the pandemic alert scenarios; (c) possible ticketing strategies for PT users have been investigated based on the HCM findings, searching for the configuration of safety measures to ensure that users accept a 100% allowed capacity on board during moderate/high pandemic scenarios without varying the price, as well as the price variations needed to stay in an indifference range of the utility in restricted conditions of the service; (d) the acceptability of safety measures has been assessed through a simulation exercise, finding that non-vaccinated travellers are 2.6 and 2.1 times more willing to accept a full capacity of the buses/trains on board than vaccinated people if subscribers or not, respectively.

1. Background and motivation

The COronaVIrus Disease 19 (COVID)-19 exploded in Wuhan (China) in November 2019 and was declared a global pandemic by

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the World Health Organization (WHO) on 11th March 2020. The first country to experience COVID-19 in a significant way outside China was Italy, where the first infection (patient zero) was declared on 21st February 2020. The implementation of the lockdown and the first significant increase in infection was the first of many phases in Italy, which was followed by the introduction of the colouring system of Italian regions (depending on the extent of the pandemic), the implementation of green pass certification to access facilities and the gradual introduction of the vaccines. Since 2022 onwards, with a share of 1st dose vaccinated exceeding 90 %, Italy has moved to a new phase, where the imperative is to live with the virus and be prepared for other emergencies. Indeed, some researchers argue that COVID-19 is in a transition towards an endemic phase (Biancolella et al., 2022). However, the consequences of the pandemic are still evident in many fields. In terms of mobility, even though a high vaccine penetration has been achieved and the WHO has declared the end of the emergency in May 2023, at the beginning of 2024, the PT in Italy still registers a significant contraction in PT passenger volumes. Indeed, according to the 1st-trimester report of the National Observatory for Passengers and Freight Mobility (MIT, 2024), total PT volumes in Italy are stable w.r.t. 2023 and still significantly lower (around 20% less) than the pre-pandemic period. This suggests that the COVID-19 experience has been traumatic, probably inducing people still now to prefer uncrowded spaces, pay more attention to the safety of shared vehicles and have an increased preference for work-from-home (WFH), when possible. Furthermore, the concern of WHO for future emergency scenarios is testified by many documents (see e.g. the scenarios presented in World Health Organisation, 2022). This can be found also in the recent revision of the Emergency Response Framework (World Health Organization, 2024a), the attempt to revise past International Health Regulations (World Health Organization, 2024b), the current interest in urging countries to adhere to the Global Digital Health Certification Network (World Health Organization, 2024c) and the words of the Director General of WHO at the World Government Summit in February 2024, who stated that "*a new pandemic is only a matter of when, not if*", where he used the term "Disease X" to indicate the next pandemic which will occur in the future for some cause unknown today (Ghebreyesus, 2024).

Concerning mobility by public transport (PT), several authors started to talk about the hypothetical "New Normal" scenario (Corazza et al., 2021; Vickerman, 2021; Zafri et al., 2023), suggesting that mobility habits were expected to rearrange differently than before the pandemic. All these considerations suggest that both institutions, at a higher level, and mobility providers, at a lower level, must be prepared for the possible future evolution of other pandemic scenarios. Authors such as Mulley et al. (2020), Hensher (2020) and Vickerman (2021), in the early stages of the pandemic, hypothesised that transport users would have shown reluctance to share transport in the future and an increasing focus on social distancing. Corazza and Musso (2021) indicated that policymakers must consider the growing trend towards the so-called "unsharing". Also, the literature starting from 2022 has expressed concern for the return of the PT to the pre-pandemic conditions (e.g. Sharifi, 2022; de Palma et al., 2022), and the very few studies investigating transport users preferences and attitudes in periods that can be reasonably deemed as "post-pandemic" still highlighted a clear sensitivity of users to hygiene, cleanliness of vehicles, the eventual vaccine certification and a general concern for sharing spaces (as discussed in Section 2 and Section 6.3).

This paper aims to assess preferences and attitudes for PT use and safety vehicle characteristics in the post-vaccine period – by meaning with the latter expression a period were vaccines were very highly penetrated within the population – and to provide a tool for incorporating the changes in such preferences and attitudes in the event of future pandemic scenarios. A panel-stated preference (SP) survey with attitudinal questions was disseminated among PT users of the city of Naples (Italy) in two waves, during the spring and early summer of 2022, i.e. in a time horizon where COVID-19 vaccines were already highly penetrated in the population (see Section 4.2). The survey aimed to assess the preferences for onboard vehicle safety characteristics as a function of unobservable individual traits. The results have been obtained through a Hybrid Choice Model (HCM), where preferences for onboard vehicle characteristics have been partially explained by latent psychological factors. Willingness-to-pay (WTP) and sensitivity of willingness to adopt PT under certain safety measures configurations have been tested in three different hypothetical pandemic alert scenarios and several guidance for PT companies have been provided. In particular, optimal pricing schemes in the event of new moderate/high pandemic alert scenarios have been derived through a simulation exercise, based on the HCM findings. Notably, this poses both equity and economic issues, in that, for instance, ensuring a social distancing on board, which generally reflects into a reduced capacity of the service, may reflect in disadvantages experienced by specific groups of travellers (see Section 7.4). In addition, there are safety measures that are relatively less costly for the company to implement (e.g. checking the vaccination certification of on-board staff), others represent specific items of expenditure (e.g. increasing the disinfection frequency of vehicles, providing hand disinfectants, equipping vehicles with specific systems for air exchange and recirculation to filter out viruses and bacteria), and still others may be only seemingly cost-free (e.g. restricting on-board capacity may result in the need for more frequent service).

Several reasons motivated the analysis of this paper. First, PT has always represented the core of policies that incentivize the use of sustainable modes and the main competitor of private cars in urban areas, especially for long urban trips (being active modes the core of sustainable policies on short trips, such as near-home / work or first-last mile ones). Therefore, PT should return to its role as the main means of countering externalities, such as emissions, road accidents and congestion.

Second, most research in the field of PT and COVID-19 has assessed the users' preferences and attitudes during lockdown periods, while very few studies investigated the post-vaccine era (e.g. from 2022 onwards), as emphasized by a very covering literature review provided in the next section and the discussion in Section 6.3. Thus, the analysis of preferences and attitudes for PT in urban areas in such a post-emergency scenario deserves particular attention, and more research in the post-vaccine context is needed, to update and/ or rewrite previous literature results. In such an uncertain scenario, individual latent traits are supposed to play a crucial role in explaining, at least partly, the preference and WTP heterogeneity of users, as the recent literature on transport and COVID-19 suggests. In particular, Zafri et al. (2023) indicated that risk perception and trust in policy measures are expected to have a strong impact on PT usage even in hypothetical "New Normal" situations. According to the literature, we assume that latent traits such as pandemic concern (in terms of awareness and attitude towards the information about the disease spread), trust/distrust in city services (for which the PT plays a key role) and national government actions (given that the national government actions are the main ones to contrast the spread of the disease) can be important factors in explaining travel behaviour in general, and preferences for onboard safety measures of PT in particular. The policy implications derived from this study allow us to consider the economic impact of the analysed latent traits, through several simulation exercises (see Section 7).

Third, the analysed case study represents a typical example of a car-dominant city, where the rearrangement of travel habits could be an unprecedented occasion to reshape urban mobility more sustainably (more details in Section 3 on the analysed case study).

The remainder of the paper is organized as follows: Section 2 provides an overview of the literature on mobility and COVID-19-related problems, with a special focus on studies resorting to discrete choice analysis and HCMs; Section 3 provides some details of the PT supply in the city of Naples; Section 4 describes the survey design and the detail of the sample analysed; Section 5 illustrates the modelling framework implemented for the case study; Section 6 shows the results of the analysis on the data collected, and discusses results in the light of previous literature referred to pandemic and post-pandemic periods; Section 7 provides some insights on WTP as a function of attitudes, the optimal pricing schemes in different future pandemic alert scenarios and sensitivity in PT use when varying relevant characteristics, which allowed deriving many useful policy implications for PT service providers and policy-makers based on the HCM findings; Section 8 draws the conclusions, defines the limitations of the present study and provides some suggestions for future research steps needed to update/transfer the current findings; Appendix A reports some more details on the pandemic evolution in the Italy and the Campania region.

2. Literature review

Earlier studies on the impact of COVID-19 on transport systems have been taking place since the early months of the pandemic. Growing concern about the virus has prompted researchers from around the world to step in and apply their expertise and to emphasize challenges/issues related to PT use, both from users' and company/policy-makers standpoint. As early as the spring of 2020, the first scientometric analyses began to follow (see Haghani et al., 2020). The work of Gkiotsalitis and Cats (2021) was among the first to identify the main problems that would concern PT operationalization. In this new phase, researchers are summarizing the lessons learned from the lockdowns and restrictions periods. For instance, de Palma et al. (2022) analysed the impact that the first 18 months of the pandemic had on various activities, such as lifestyle, teleshopping, teleworking, air pollution, and road transportation. Some studies are also trying to predict travel behaviour in light of a "New Normal" scenario (e.g. Vickerman, 2021).

However, during the last few years, many contributions and case studies have emphasized the need to look at the problem from the users' perspective. Indeed, since the first months of the pandemic alert, there has been a drastic decrease in total travel time (Borkowski et al., 2021), especially for what concerns PT (Beck et al., 2020). The current section revises the state-of-the-art of transport and COVID-19-related problems, with a focus on the works analysing the issue by resorting to discrete choice analysis. In particular, Section 2.1 provides a literature review on the works resorting to standard discrete choice models (i.e. without the incorporation of latent variables), while Section 2.2 focuses on the studies in the literature that analyse both choices and attitudinal data through HCM.

2.1. Discrete choice analysis and transport-related problems in the time of COVID-19

Econometric models have been widely applied to model several types of outcomes in COVID-19 time. As per established practice in transportation engineering, many researchers have made use of choice analyses, mainly resorting to discrete choice models, on revealed preference (*RP*) and/or stated preference (*SP*) data to address specific transport problems. Haghani et al. (2022), in particular, provided the first detailed assessment of the use of discrete choice experiments (*DCE*) in the context of COVID-19. Specifically, the authors considered only those studies that used SP-type data as of 2021, expanding the research to include sectors such as health, transport, tourism and business. Transportation was found to be the second largest sector in terms of the number of contributions after health.

Since that systematic review, many other contributions have followed in the literature. In particular, discrete choice analysis has been resorted to for many choice problems in COVID-19 transport-related problems, namely: change in activity chain (Liu et al., 2021), route choice (Marra et al., 2022; Shelat et al., 2022b), route choice in urban rail transit (Xu et al., 2024), the value of crowding (Aghabayk et al., 2021; Bansal et al., 2022; Cho and Park, 2021; Shelat et al., 2022a;Drabicki et al., 2023; Hong et al., 2024; Karatsoli et al., 2024; Pollock et al., 2024; Singh et al., 2023a; Yap et al., 2023), the value of reliability (Cherry et al., 2021), willingness to share flood evacuation riders (Borowski et al., 2021), willingness to trip instead of smart working (Dias et al., 2021; Müller and Wittmer, 2023) or, conversely, WFH choice (Beck et al., 2020; Beck et al., 2020; Asgari et al., 2023; Baldassa et al., 2023; Hensher et al., 2023; Hernández-Tamurejo et al., 2024; Liang et al., 2023; Wang et al., 2024) and decisions from bus operators to close a customized bus line (Shen et al., 2024). However, the vast majority of choice problems investigated in the literature concern the travel mode choice. Indeed, early statistical evidence showed that the risk of spread of contagions resulted in a sharp contraction in demand and a significant modal shift from shared modes (mainly PT) to private modes (mainly cars). In any case, many studies have looked at specific travel modes, such as urban active modes (e.g. Bergantino et al. (2021), on-demand services (Ren et al., 2023), air transportation (Chen et al., 2022c; Manca et al., 2021; Manca et al., 2023; Singh et al., 2023b), or more innovative mobility services such as shared autonomous vehicles (Nickkar et al., 2023) or Mobility-as-a-Service (Cisterna et al., 2022; Baldassa et al., 2022). These studies aimed to investigate micro-economic characteristics such as WTPs, demand elasticity and marginal rate of substitutions. Several geographical contexts have been analysed in terms of mode choice preferences with pure discrete choice analysis (i.e. without the incorporation of psychological variables), such as: Australia (Xiang et al., 2023), Bangladesh (Zannat et al., 2021; Mahmud et al., 2024), Brazil (Costa et al., 2022), Cambodia and Laos (Phandanouvong et al., 2021), Canada (Mashrur et al., 2022;Liu et al., 2023; Loa and Habib, 2023;

Terry and Bachmann, 2023), China (He et al., 2021; Luan et al., 2021; Zhang et al., 2022; He et al., 2023; Ren et al., 2023; Xiang et al., 2023; Xiao et al., 2023; Yu et al., 2023), Colombia (Alberto Ortiz-Ramirez et al., 2024), Germany (Eisenmann et al., 2021; Filgueiras et al., 2024), Greece (Fafoutellis et al., 2022; Nikiforiadis et al., 2022; Simović et al., 2021), Hong Kong (Chen et al., 2024), Iran (Shaer and Haghshenas, 2021), India (Zannat et al., 2021; Aaditya and Rahul, 2023; Rankavat et al., 2023), Italy (Bergantino et al., 2021; Ceccato et al., 2022, 2021; Piras et al., 2022; Rotaris et al., 2022; Lodi et al., 2024; Rotaris et al., 2023), Korea (Eom et al., 2022), the Netherlands (C. Chen et al., 2022b), Pakistan (Abdullah et al., 2022; Xu et al., 2021), South-East European countries (Simović et al., 2021), Taiwan (Jou et al., 2022), UK (Ulahannan and Birrell, 2022) and USA (Qu et al., 2022; Battifarano and Qian, 2023; Cai et al., 2024; Cherry et al., 2023; Deka and Liu, 2024; Khatun and Saphores, 2023; Pike, 2023). All the works emphasized different aspects, such as the increasing propension to private modes during lockdown periods, the reduced frequency of use of shared modes and the attention to factors such as social distancing, cleanliness of the vehicles and air quality on board. These aspects have been also deemed as crucial in determining users' preferences in general review articles (Calderón Peralvo et al., 2022; De Vos, 2020; Gutiérrez et al., 2021; Shortall et al., 2022).

The current work directly investigates preferences for specific policy actions that a PT provider may implement, mainly in terms of onboard PT vehicle characteristics and safety measures in different pandemic alert scenarios. Differently from mode choice experiments, respondents in this study faced choice scenarios where the option was represented by a certain configuration of safety measures, i.e. actions that could be implemented by the PT provider, as a potential consequence of policy actions by institutions or by initiative of the company itself. The goal is to assess the acceptability of these measures, which is similar in aim to what was investigated by Awad-Núñez et al., (2021a,2021b) and Bwambale et al. (2023). Awad-Núñez et al., (2021a, 2021b) analysed the same sample of transport users in Spain during the spring of 2020, but with different methods. In the first study, they used a two-step model to analyse the willingness to use their habitual mode and the WTP more than before COVID-19, as an ordered percentage, for special sanitizing measures (e.g. cleanliness/sanitising on board PT vehicles and taxi/ride-hailing means, covers for handlebars in bike/scooter sharing etc). They found that PT users showed higher wiling to use the PT and WTP for increasing the supply to avoid crowding and increasing the vehicle sanitising. In the second study, they used a logistic regression to assess willingness to continue using car, to accept pedestrian/bike areas and to shift to more sustainable modes. Bwambale et al. (2023) have assessed, in particular, the impact of social distancing measures (half capacity) and safety measures on board PT vehicles, with a focus on hand sanitisers on board and daily disinfection frequency.

The current work has several differences from those above. First, it refers to a period that can be deemed as post-pandemic and post-vaccine, as it is characterized by a very high vaccine penetration. Second, it resorts to attitudinal data to better explain the preferences of users and WTPs. Third, it incorporates different hypothetical pandemic alert scenarios (low, moderate, high) and considers different variables, which take into account the evolution of safety measures during the first two years of the pandemic, e.g. the green pass certification and the use of air exchange/filtering systems.

2.2. Transport-related problems and hybrid choice models (HCMs) at the time of COVID-19

As pointed out by many authors, latent traits that are not directly observable, such as perceived safety, risk of contracting infection, perceived quality, and trust in policy actions to counter the spread significantly impacted users' preferences and microeconomic characteristics (e.g. WTPs). It is, therefore, safe to assume that, in such a scenario, the incorporation of latent variables into standard econometric models is an important tool in the hands of choice analysts, as models that do not account for such psychological aspects would result in significant biases in estimates. This study aligns with that consideration and analyses the preferences and attitudes of PT users in the city of Naples, using a Hybrid Choice Model (HCM). Over the past years, many authors have made use of HCMs to better understand the cognitive mechanisms underlying users' choices. We have searched the Scopus database to determine all studies that have analysed travel behaviour during the pandemic using HCMs. Downstream to a filter occurred after reading the papers and ensuring they implemented HCMs, 18 studies published in the period 2020–2024 have been reviewed.

The studies analysed cover different geographical areas, namely: Australia (Hensher et al., 2022), Brazil (Lucchesi et al., 2022), Canada (Liu et al., 2023), Chile (Basnak et al., 2022; Iglesias and Raveau, 2024), China (Zhang et al., 2022), Colombia (Ortiz-Ramirez et al., 2024), India (Aaditya and Rahul, 2021; Aaditya and Rahul, 2023), Italy (Scorrano and Danielis, 2021), Israel (Soria et al., 2023), the Netherlands (Ashkrof et al., 2022; C. Chen et al., 2022a), Santo Domingo (Puello, 2022), Taiwan (Cheng and Lai, 2024) and USA (Ashkrof et al., 2022; Rossetti et al., 2024). The work by Manca et al. (2023) differs from the previous ones in that the authors analysed the behaviour of air passengers, considering respondents from airports in London, New York City, Sao Paulo and Shanghai.

First, almost all studies incorporating psychological factors included safety/risk perception related to COVID-19 directly or indirectly. Concerning the second category, i.e. studies that indirectly embed the effect of the risk perception towards the disease, for instance, Balbontin et al. (2022) included the PT concern in their study on WFH preferences, while Basnak et al (2022) included safety, vehicle and station cleanliness, which are strictly related to the feelings of users towards the COVID-19. The current study also considers the effect of the pandemic concern on PT users, but we differed from all the reviewed studies in that we analysed the pandemic concern while interacting with onboard vehicle attributes. Second, 11 out of 18 studies were focussed on mode choice behaviour, with a general concern on the demand elasticity for both PT and active modes. The current study differs in that it investigates the preferences for policy actions from the local/national institutions and PT providers for onboard vehicle safety measures, considering exclusively the PT users. Third, most importantly, all the studies have been implemented during lockdowns or high pandemic periods, ranging from time horizons from early spring of 2020 to Autumn of 2021, while none of the analysed studies has assessed the preferences and attitudes of transport users in the post-vaccine era. The most recent surveys investigating preferences and psychological latent factors are those by Liu et al. (2023), who compared data from two periods, namely July 2020 and July 2021, on mode choice preferences in Toronto (Canada), with main reference to ride-sourcing, and Aaditya and Rahul (2023), who referred to data collected in October 2021 in Odisha (India), concerning commute trip frequency. The latter study, which referred to a period where vaccines had good penetration in the Indian population, still emphasised a significant residual fear of infection by Indian commuters.

Two studies followed methodological approaches that are somewhat similar to those proposed in the current study. The first one is that of Chen et al (2022), which considered three different lockdown policy contexts, each one referring to a pandemic alert situation and concerned colouring scale. Furthermore, we considered some attributes (e.g. allowed per cent of passengers on board, the disinfection frequency and hand rubs) and latent factors (perceived risk) in common with their study. However, several substantial differences remain. The study by Chen et al (2022) investigated the mode choice behaviour through a labelled SP survey, more appropriate to assess demand elasticity for each mode (as the authors did). The current study focuses on in-vehicle safety measures, investigated in turn through an unlabelled stated choice experiment, which is more reliable in assessing WTPs and the relative importance of attributes (Bliemer and Rose, 2023). The pandemic situations in Chen et al (2022) were more apt to indicate policy restrictions, while in the current study, we explicitly refer to pandemic alert scenarios both in terms of disease spread and hospital pressure, referring to specific time intervals experienced by users during pandemic peaks in the region. Furthermore, the authors used both the pandemic situations contexts and latent factors only interacting with alternative specific constants (ASCs), whereas in the current study, preferences for each onboard characteristic have been differentiated by pandemic context and interacted with the analysed latent factors, to assess how pandemic alert and psychological traits affect preference heterogeneity and WTPs. This implies that trade-offs, in general, and WTPs, in particular, did not depend upon the latent factors and pandemic context in Chen et al. (2022), while our study introduces such a feature in the modelling framework. Finally, as previously emphasized, the work by Chen et al (2022) concerns the lockdown pandemic context, with a survey disseminated in December 2020-January 2021, while the current study investigates the PT preferences and attitudes downstream of a high vaccine penetration. The second case where we found similarities in the methodology is represented by the works by Manca et al (2023), which represent the only other examples of HCM with unlabelled DCE but referred to a very different choice context (air itinerary) and different attributes/latent factors.

In summary, the literature review emphasizes that the current study distinguishes itself from the other studies resorting to HCMs, apart from the analysed geographical context, mainly for the following features:

- The analysis of PT users' preferences and attitudes toward safety measures on board the PT vehicles in a context where vaccines were highly penetrated in the population (spring-summer 2022);
- analysis of the WTPs for onboard safety characteristics in different hypothetical pandemic situations and investigation of the capability of latent factors in explaining WTPs heterogeneity;
- the optimal pricing schemes based on the HCM results, when varying relevant on-board characteristics (e.g. allowed occupancy rate) and the pandemic alert (moderate, high);
- the sensitivity of important PT users' segments (e.g. fully vaccinated or not, subscribers or not) when varying on board relevant characteristics (e.g. allowed capacity on board, green pass check at the entrance).

This allows obtaining a useful tool for both policymakers and transport companies operating in the analysed territory, in that it allows providing both ticketing and/or service design strategies without ticket variation, as well as detecting the segments of users who are more willing to accept certain safety measure implementations, as discussed in Section 7.

3. Case study

The city of Naples is the third largest Italian city by population (914,873 residents) and land area (117.27 km2) and has the highest population density (7801.42 residents/Km2) among large Italian cities. The whole metropolitan city of Naples has more than 3 million residents and contains more than half of the Campania region's inhabitants.

The PT system of the metropolitan city of Naples has several transport companies providing rail, road, and funicular services. The companies operating urban road transport are: Azienda Napoletana per la Mobilità (ANM), Ente Autonomo Volturno (EAV), Compagnia Trasporti Pubblici di Napoli (CTP) and Sicurezza Trasporti Autolinee (SITA Sud). The companies providing rail transportation

Table 1
PT tariff system in the city of Naples. (legend: S = single company; I = integrated between different companies operating in the city of Naples).

Tickets		Subscriptions							
Single trip	Integrated fare (60 min)	1-day		7-days		Month		1-year standard	
S	I	S	I	S	I	S	I	S	I
1.10 € 1.30 €	1.60 €	3.50 €	4.50 €	12.50 €	16.00 €	35.00 €	42.00 €	235.20 €	294.00 €

Subscriptions							
1-year standard subsidised (ISEE < 12.500 €)		1-year standard over 65 subsidised (ISEE < 10.000 €)		1-year students		1-year students subsidised (ISEE < 12.500 €)	
S	I	S	I	S	I	S	I
211.70 €	235.20 €	176.40 €	22.50 €	164.60 €	176.40 €	117.60 €	132.30 €

services are Trenitalia, the Società per il Servizio di Servizi Pubblici Anonima (SEPSA), Circumvesuviana and Metrocampania Nord-Est. Table 1 reports the current fare system in the city of Naples.

Data on current and planned PT supply in the city provide two different pictures. On the one hand, the current PT supply appears inefficient, in terms of operating costs sustained by transport companies, and ineffective, in terms of average load factors (see Papola et al., 2017). On the other hand, all the planned interventions aim to make the city of Naples one of the most equipped in the Italian context in the medium to long term. Further details are provided below.

Currently, rail transportation includes 2 subway lines (line 1 and line 6), 1 rail pass (line 2), 4 funiculars, 2 open-air railway lines (Cumana and Circumflegrea), and 6 other railway lines that provide both intercity and urban transportation services (2 of which correspond are also referred to as subway lines 3 and 4). Road transport includes over 130 bus lines (123 of which are operated by the ANM company). Finally, there is the presence of 3 escalators. According to data from the company Moovit, the PT in the city of Naples suffers from supply efficiency problems. In fact, according to the company's estimates, the average waiting time amounts to about 20 min (the highest value among Italian cities), with average travel times of 38 min (second in Italy, after Rome, which has an extension that is 10 times greater, and Milan, which has an almost double extension), and average distances travelled equal to 5.3 km (last of the top 5 Italian cities). In addition, although single-trip ticket prices are the lowest among Italian cities, there is an estimated 59 % of ticket payment evasion on board buses. Finally, according to Banca Ifis's Market Watch report (Banca Ifis, 2022), PT accounts only for 17 % of total trips in Naples. According to Moovit (2022), Naples PT users declared themselves also unsatisfied with the safety and cleanliness of vehicles and the same report notes that while about 30 % of users stated they use less PT in the city, only 12.3 % stated they use more PT than before the main pandemic waves.

In any case, Naples is one of the cities that is investing more public funding in new PT infrastructure in Italy, leading to the total presence of 9 metro lines, with a total length of 90 km (about 1 km per 10,000 residents), more than 100 metro stations and 20 interchange stations. Thus, planners' effort to equip the city to enhance PT with more widespread services is evident. In addition, especially on the rail lines, transport companies are putting efforts to improve the perceived quality of PT, through the modernization of the vehicle fleet and with the so-called art stations initiative. To summarize, PT in the city aims to take away much modal market share from other travel modes and improve its perceived attractiveness to transport users in the medium term. As Naples users are unsatisfied with vehicle cleanliness and safety, improving ticketing strategies for PT users and quantifying users' preferences and attitudes is important to implement measures to enhance the service, especially in the event of further possible emergencies.

During the main pandemic waves (2020–2021) several measures were adopted to counter the virus spread. Reconstructing the actual set of safety measures on board in real past pandemic alert scenarios is not an easy task, since both the decrees of the Prime Minister and orders of the Governor of the Campania region were released continuously and adapted to the pandemic evolution dynamically. In addition, each supplier company was able to implement its on-board security measures independently, adapting to the kind of vehicles and equipment owned. However, in pandemic alert scenarios equivalent to that presented as low, the on-board occupancy rate was mostly allowed at 100 per cent, whereas in moderate and high pandemic alert contexts, restrictions of on-board capacity occurred at values of around 50 per cent (1-metre spacing required). National directives also required PT companies to ensure the use of a mask on board. Showing the green pass certification, instead, has been considered mandatory until spring 2022, i.e. until the period in which the survey was disseminated.

4. Data collection

4.1. Survey structure

The survey consisted of 6 main parts: (1) preliminary questions to direct the SP scenarios, (2) SP survey, (3) ex-post questions on the processing strategies of the SP variables, (4) attitudinal questionnaire, (5) travel habits of the respondent and his/her household before, during and after the pandemic, (6) socio-demographic characteristics of the respondent and his/her household.

Preliminary questions) The first part consisted of two preliminary questions on the type of PT mode habitually used by the respondent (bus, train, or other, such as funicular) and the ticket title used among the following 8 base fare schemes: single trip, 90-minute integrated, daily business, daily integrated, monthly business, monthly integrated, annual business, annual integrated. The intermediate options of the fare system have been already shown in Table 1. Note that the integrated ticket allows to travel on board vehicles of different PT companies and for multiple trips, within the limits granted by the ticket duration. These questions allow the customization of the SP scenarios mentioned in the second step.

SP survey) In the SP survey, each respondent faced 6 unlabelled hypothetical scenarios. In each hypothetical scenario, the respondent is asked to indicate a preference between two generic alternatives (*A* and *B*), with an opt-out option, the latter presented as "neither of them / I prefer not to travel by PT", to not constrain the user to make a choice that could bias successive model's estimates. We opted to include a maximum of two trip options, as according to Zhang and Adamowicz (2011) and Mariel and Meyerhoff (2016), including three or more options would lead to artificially a decreased share of opt-out answers (non-realistic rate of choice) and biased trade-offs. Within each hypothetical scenario, 3 choice tasks are answered by respondents, i.e. the choice among the three alternatives in each one of three different pandemic alert situations labelled as follows: low (L), moderate (M) and high (H). Given the presence of three different context variables, it results not possible to indicate any of the travel options as the status quo alternative in such a survey. Before the choice tasks, we provided an example scenario and explained the three pandemic alert situations with a brief description and the aid of some pictures detecting green, orange and red semaphores, indicating in turn low, moderate and high pandemic alert situations in the Campania region. The choice to show the pandemic alert situation referring to the regional context is anchored by two considerations. First, the pandemic bulletin and the classification of the pandemic alert have been presented for each region in the official data of the Region. Second, in Italy, each region has the faculty to rule out its own health and transport-related measures, consistent with the national ones. Note that the colour map of the pandemic zones in Italy consisted of four colours, i.e. green, yellow, orange and red, where the green zone corresponds to a non-pandemic alert scenario. However, after the implementation of some focus groups, we opted to reduce the hypothetical pandemic scenarios to three, consisting of the three situations where the pandemic actually occurred. Finally, each pandemic alert has been described in terms of hospitalization rate, pressure on healthcare facilities, and the daily number of infected persons per 100'000 inhabitants, providing also a reference temporal window for each scenario. For instance, we referred to the high pandemic alert (red semaphore) to the autumn 2020 – winter 2021 period, where the highest values of hospitalization rates and dead persons were registered in the region (see Appendix A). We chose not to introduce other SP variables indicating the health situation, such as vaccination rate (as did, for instance, in Bansal et al, 2022), because the vaccines were already highly spread out in the population at the time of the survey (see Section 4.2). Nonetheless, the effectiveness of the vaccines in contrasting the major symptoms could have been treated as a context variable, but the evidence of the vaccination effects, as testified in the highly reduced ratio of death per infection in 2022, suggested that vaccines were already proven to be very effective. We did not include the travel time between scenarios, to focus on the safety measures on board, rather than on level-of-service characteristics. Indeed, change in travel time would be obtained in the long-term scenario, as a result of policy actions aiming at reducing congestion, as the bus PT supply is prevailingly implemented in a promiscuous venue in Naples, while rail supply would require further investments in vehicle fleet modernization, which requires a long-term time horizon. Finally, we did not include any other safety measures that can be imposed by the national government, such as compulsory masks, as the focus of this study is on the implementation of onboard safety measures from the transport company side.

Each alternative is described through the following 6 variables: the ticket price, allowed capacity on board (due to mobility restrictions), frequency of disinfection and cleaning, presence of sanitizer, the possibility of changing the air on board vehicles and the type of green certification check. We summarized the attribute levels in Table 2, where a description of the attributes has been reported in the second column, consistent with the description made before presenting the scenarios to the respondents. Concerning the ticket price, the SP scenarios are pivoted with a pre-saved library of scenarios (more details below), as the absolute value of the ticket price proposed in each scenario is derived from the answer to the two preliminary questions described above. We indicated the occupancy rate in terms of total allowable persons on board, without specifying whether they were standing or sitting spaces, as both rail and bus vehicles in the city of Naples have a very small number of seats. Thus, participants in the focus group indicated that they did not perceive the indication of whether the allowable boarding place was in a seat or not as useful.

The SP scenarios were designed with a D-efficient design (Rose and Bliemer, 2009), using Ngene software (ChoiceMetrics, 2012). The D-efficient design aims to combine the attribute levels in such a way as to maximize their information content, using the minimum of the determinant of the asymptotic variance/covariance matrix of the model estimates as a measure of efficiency. The likelihood model against which the scenarios were designed is the MNL and the prior values of the coefficients were deduced from a pilot study conducted on a small number of respondents, to which a set of scenarios obtained by an orthogonal design was administered. For each type of vehicle (bus, train, or other) and ticket, a total of 12 scenarios were generated, dividing the generated scenarios into two blocks of 6 scenarios each, which were proposed to the respondents of the two waves, respectively, to increase the variability in attribute levels and the degrees of freedom of the experimental design.

Fig. 1 illustrates an example of SP choice scenario referred to people who indicated to generally buy a single journey ticket, with the preliminary description of the three pandemic alert situations. Respondents were asked to indicate their choice between the three options (A, B and opt-out) in each one of the three described pandemic alert situations (low, moderate, high).

In summarizing:

- for each respondent, a total amount of 6 scenarios * 3 choice tasks (low, moderate and high pandemic) = 18 choice tasks per respondent have been collected;
- The 6 scenarios shown to respondents in Wave 1 are different from those shown to respondents in Wave 2 (blocking).

Table 2
SP survey: attribute levels.

Attribute	Description	Levels
Ticket price	The price has a status quo level representing what respondents habitually spend for travelling by PT (e.g. single trip, integrated ticket, daily subscription etc). Variations in percentage w.r.t. to the status quo were shown to the respondents.	−20 %, −10 %, 0 (status quo), + 10 %, + 20 %
Occupancy rate [%]	It represents the allowed capacity on board the vehicles, indicated as the percentage of the maximum allowed in standard conditions (e.g. 80 passengers per bus, 200 passengers per wagon).	50, 75, 100
Disinfection frequency [times/day]	It indicates the information to users concerning the number of daily sanitisations of the vehicles.	1,2,3
In-vehicle sanitizer	It indicates the eventual presence on board of at least one hand sanitizer gel dispenser.	1 (Yes), 0 (No; base)
Air exchange/filtering	It indicates the possibility of air exchange on board the vehicles. In particular, the attribute indicates the quality of the air recirculation, achieved through a system that allows complete air exchange in a few minutes, thanks to special filters that retain viruses, bacteria and allergens.	1 (Yes), 0 (No; base)
Green pass check modality	It indicates the type of check of the vaccination certification by the personnel on board through Q.R. code.	1 = at vehicle entrance, 0 = Inside vehicle at random (base)

	Configuration of safety measures on bus - option A	Configuration of safety measures on bus - option B	Neither of them
Ticket price	1.10 €	0.80 €	-
Allowed capacity on board [% o total seats]	100%	50%	-
Daily disinfection frequency of vehicles	Twice a day	Twice a day	-
Hand sanitizer on board	No	Yes	-
Air exchange on board	Yes	No	-
Green pass check	Before boarding (entrance)	On board (at random)	-
Low pandemic alert	○	○	○
Moderate pandemic alert	○	○	○
High pandemic alert	○	○	○

Fig. 1. SP choice scenario example (translated from Italian) for the single-ticket trip.

Notice that, since the literature suggests often a number of scenarios greater than 6 (e.g. Oehlmann et al., 2017) and since generally the presence of multiple choice tasks for each scenario is not considered to increase significantly the cognitive burden of the respondents (e.g. as in the cases respondents are asked to indicate their preference both in the presence of the opt-out option and as a forced choice), it can be safely concluded that the proposed stated choice experiment does not lead to excessive fatigue.

Attribute attendance ex-post valuation) Downstream of the SP part of the questionnaire, each respondent was asked to indicate the type of strategy used to process the choice tasks among the following three ones: considering all scenario variables (total attribute-attendance), considering only a subset of variables (partial attribute-attendance), and responding randomly (non-attendance). In the second case, the respondent is provided with a grid to indicate the sub-set of the attributes considered. This information has been accounted for in the model described in Section 5, to reduce estimation bias due to attribute-non-attendance. In the data analysis presented in Section 6, only respondents with the first two strategies have been included, deleting respondents who admitted to having chosen randomly.

Attitudinal questions) We showed 15 psycho-attitudinal statements, asking the respondent to indicate his or her agreement on a 5-point Likert scale (1 = "not at all agree", 2 = "little agree", 3="neither agree nor disagree", 4 = "somewhat agree", 5 = "completely agree"). Statements 1–3 were intended to investigate the respondent's sensitivity to environmental issues. Statements 4–6 represented pandemic-related statements, where the fourth and fifth concerned the respondent's level of information and sensitivity to the topic of the COVID-19 pandemic, while the sixth statement concerned the respondent's willingness to share transport vehicles with strangers. Statements 7–9 concerned the attitude to behave appropriately towards the community, with general statements on civic education and specific statements on the willingness to adopt behaviours appropriate to the pandemic situation. Statements 10–12 concerned the degree of satisfaction with and trust in local (Naples municipality, Campania region) or national (state, ministries) institutions, in terms of actions taken to make city services more efficient and to implement measures to counter the spread of the virus. Finally, statements 13–15 aimed to investigate the degree of general satisfaction with the public services offered by the city of Naples. In the attitudinal statements, to avoid the framing effect (Druckman, 2001; Tversky and Kahneman, 1985), we declined some statements either positively (e.g., "In my travels, I prefer means that do not worsen air quality.") and others negatively (e.g., "When I choose to travel by local public transport, I do not think about the reduction in environmental impact resulting from my choice."), to keep the respondent's attention. In general, we mixed statements apt to investigate general attitudes, i.e. not related to PT or travel behaviour, and specific attitudes, i.e. strictly related to PT use. Indeed, as widely recognized by literature, general attitudes influence travel preferences (Kroesen et al., 2017). Finally, note that the attitudinal part has been proposed after the SP part so as not to induce bias in stated choices (Bliemer and Rose, 2024).

Travel Habits) In the fifth section, respondents were asked to indicate some characteristics related to their mobility habits and household vehicle ownership. Specifically, each respondent was asked to provide information on driver's license ownership, whether he/she was a regular driver, the number of cars and motorcycles owned by the household, the frequency of use and the prevailing travel purpose when using before/during and after the most stringent pandemic scenario restrictions (autumn 2020, winter 2021), and whether the respondent had some PT incentives or ticket refunding.

Socio-demographic characteristics) In the last section, each respondent was asked to indicate other socio-demographic characteristics of his/her household. Specifically, the respondent was asked to provide information on gender, age, current and pre-pandemic occupation, education level, household income level (including an opt-out option), household size and personal vaccination situation. The question about the personal vaccination status includes six possible situations (for more details on the vaccine options, see Appendix A):

- booster vaccine dose (3rd dose for the main vaccines Pfizer/BioNTech, Moderna and AstraZeneca, 2nd dose for Johnson & Johnson);

- 2 vaccine doses for the main vaccines (1 for Johnson&Johnson) in less than 120 days;
- 2 vaccine doses for the main vaccines (1 for Johnson&Johnson) in more than 120 days;
- Less than 2 vaccine doses (except for Johnson&Johnson);
- No vaccine dose;
- Opt-out option.

Note that the first two options allow for the green pass ownership, unless a technical time of some weeks in receiving the certification from the Italian Ministry of Health, while the next three options other situations preclude the possibility of having the green pass certification. We preferred to ask for the vaccine situation rather than the green pass ownership, in such a way as not to exclude people with a complete vaccination status but with no green pass for technical reasons (i.e. not-completed interim time required for the national health care system to appear as a vaccinated person, technical problems etc). The treatment of the vaccines as individual information is due to the consideration that: a) the survey has been disseminated in a period where vaccinations were highly penetrated within the population (see Section 4.2), thus respondents were not asked to indicate their preferences in different vaccine penetrations contexts (e.g. as in Bansal et al., 2022); b) the vaccinations were already proven to be effective to counter the major symptoms, in that the observed ratio deaths per infection was way lower than earlier pandemic phases (see Appendix A).

The framing of the questions has been a matter of confrontations with the company and focus groups. For example, asking for personal information (e.g. past experiences of infection, past family events) was discarded, as these were considered sensitive questions. The survey questions were presented in such a way as not to be so direct as to make the respondent uncomfortable, but direct enough to investigate their preferences and attitudes regarding the specific topic under analysis, i.e. the preferences and attitudes towards mobility with PT.

4.2. Data sample

A Computer Assisted Web Interview (*CAWI*) survey was disseminated in 2 waves through the ANM company's social media channels, the first of which covers the period from April 27th to May 19th, 2022, and the second from June 27th to August 12th, 2022. As will be described above, a different set of 6 SP scenarios (18 total choice tasks) was proposed to the respondent within each wave. We provided a summary of the socio-demographic characteristics of the sample analysed in Table 3.

The survey has thus been based on an opportunistic sample strategy. We note that there is the presence of some over-represented segments of citizens, such as young and graduates/post-graduates people, while elder people (over 50) are under-represented. The same occurs for employed and other categories. This suggests that we must be cautious in generalizing the results. However, to alleviate the problem of the segments over-represented, a treatment for sample bias has been introduced, by weighting the individual observations according to sample socio-demographic characteristics and those of the target population (more details in Section 5).

A total of 365 valid questionnaires were collected in two waves. After a data-cleaning process, aimed at detecting eventual anomalies in responses, such as a lack of attitudinal answers and/or declaration of a random choice strategy (see Section 4.1), we removed 33 respondents. Finally, we removed 19 more participants which chose the same alternative A or B (recurrent choice) or the opt-out alternative (serial non –participation) in all the 18 choice tasks. In summary, after the data cleaning process, 313 respondents were selected, with a total of 5634 choice observations (183 from Wave 1 and 130 from Wave 2).

The following Fig. 2 emphasizes the vaccine situation in Italy at the time of the survey. The data have been elaborated by the authors from Google News (see Mathieu et al., 2021 for a description of the open-access dataset). As it can be seen, both time intervals of the waves of the survey were characterized by high penetration of 1st dose and fully vaccinated people (note the plateau on the two concerned curves), and a considerable amount of booster doses (more than 80 % of the total doses).

5. Methodology

In this section, we analysed the data collected during the survey described in Section 4, by resorting to an HCM. The HCM allows us to simultaneously analyse stated choices and attitudinal responses in a unique framework. The pioneering work by McFadden (1986)

Table 3
Socio-demographic characteristics of the sample analysed.

Variable		Naples	Sample
Gender	Male	47.7 %	40.3 %
	Female	52.3 %	59.7 %
Age	Average age	43.3	32.7
	under 25	25.7 %	25.2 %
	25–34	11.5 %	43.5 %
	34–50	20.0 %	19.5 %
	0ver 50	42.8 %	11.8 %
Education	Secondary school or lower education	78.4 %	38 %
	Degree and post-degree	21.6 %	62 %
Occupation	Employed	35.3 %	60.1 %
	Other (students, homemakers/unemployed)	64.7 %	39.9 %

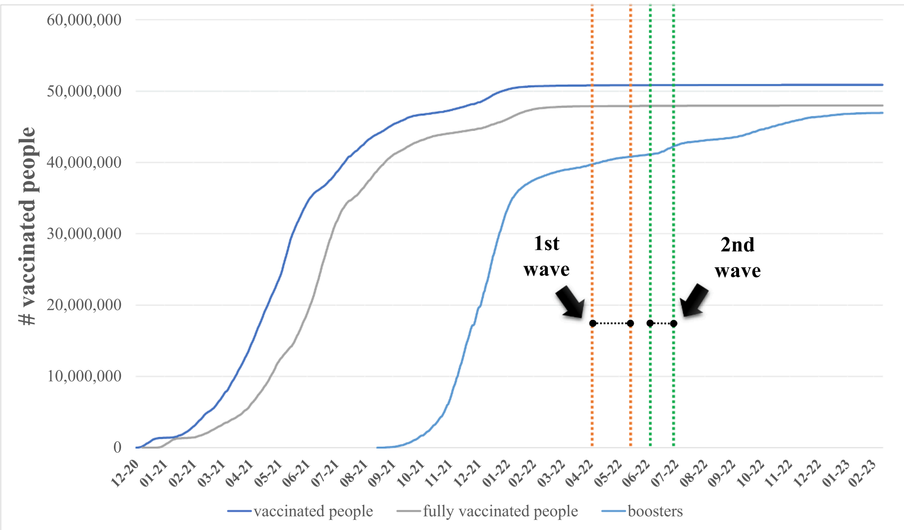


Fig. 2. Vaccination trend in Italy (elaboration of the authors from the Our World in Data, 2023 dataset).

set the basis for the inclusion of attitudinal data in discrete choice analysis, while successive significant discussions can be found in Ben-Akiva et al., (1999)2002), Walker and Ben-Akiva (2002) and more recently Abou-Zeid and Ben-Akiva (2014), Vij and Walker, (2016) and Mariel and Meyerhoff (2016).

The two macro-components of the HCM are the choice and latent variable model. Both can be characterized through structural (or causal) and measurement equation models.

Choice model) In the current work, we assume the random utility maximization (RUM) framework for the choice model component, which postulates that the respondent n facing the choice task t characterized by a choice set $C_{n,t}$ chooses the alternative i that maximizes the perceived utility $U_{i,n,t}$ among all the alternatives of the choice set. We expressed the utility of the alternatives in the WTP space as follows:

$$U_{i,n,t} = \beta_{i,n} + \beta^{*}_{pr} \cdot \left(PR_{i,n,t} + \sum_{k'} WTP^{*}_{k',n}(\lambda, \boldsymbol{LF}_n) \cdot X_{k',i,n,t} \right) + \eta_{AB,n} + \tau_{i,n,t} i = A, B \tag{1}$$

$$U_{nochoice,n,t} = \beta_{nochoice,n} + \eta_{nochoice,n} + \tau_{nochoice,n,t} \tag{2}$$

$$y_{i,n,t} = \begin{cases} 1 if U_{i,n,t} > U_{j,n,t} \forall j \in C_{n,t} \\ 0 otherwise \end{cases} \tag{3}$$

where (1)-(2) represent the utility model, i.e. the structural component of the choice model, while (3) is the measurement component of the choice model. In particular, the following terms occur within (1):

- $X_{k',i,n,t}$ represents the k' th generic individual and task-specific attribute of the alternative i, where $k' = OR$ (occupancy rate), DF (disinfection frequency), GA (gel availability on board), AF (air exchange/filtering), GP (green pass check at the entrance);
- β^{*}_{pr} represents the price coefficient;
- $WTP^{*}_{k',n}$ represents the willingness to pay for the attribute k' and individual n;
- $\beta_{i,n}$ and $\beta_{nochoice,n}$ represent the alternative specific constants (*ASCs*) for the travel and the opt-out options for each individual n, respectively;
- $\boldsymbol{LF}_n = (LF_{1,n}, \ldots, LF_{h,n}, \ldots, LF_{H,n})$ is the vector of the H latent factors $LF_{h,n}$ for the individual n;
- $\boldsymbol{\lambda} = (\lambda_1, \ldots \lambda_s, \ldots \lambda_S)$ is the vector of coefficients λ_s representing the contribution of a unitary variation of the latent factor $LF_{n,h}$ to the $WTP_{k,n}$;
- $\eta_{AB,n} \sim N(0, \sigma_{\eta_{AB}}), \eta_{nochoice,n} \sim N(0, \sigma_{\eta_{nochoice}})$ are individual-specific Normal error components, with 0 mean and standard deviation to be estimated on the data;
- $\tau_{i,n,t} \sim Gumbel(0, \theta)$ is the individual and task-specific random term of the alternative i, which is assumed as independently and identically distributed (*i.i.d.*) Gumbel across alternatives, respondents, and choice tasks, with 0 location and θ scale parameters.

The assumption on the random term $\tau_{i,n,t} \sim Gumbel(0, \theta)$ implies that the choice model is a multinomial logit (MNL; McFadden, 1974). The presence of the two error components allows for the inclusion of the correlation between the utilities of the two travel options (in particular $\eta_{AB,n}$), thus configuring a nesting Normal error component structure, and the incorporation of the panel effect, i.e.

the correlation between the utilities of each respondent alternatives across choice tasks. The inclusion of a nesting error component structure is consistent with the notion that non-opt-out alternatives could be correlated between themselves (see Campbell and Erdem, 2019; Scarpa et al., 2005).

Latent variable model) The latent variable model aims to reproduce the probability that the respondent n provides the answer m to the attitudinal statement q, as a function of the latent factors $LF_{h,n}$. The model can be represented by the following set of structural equations defining the latent factors:

$$LF_{h,n} = \gamma_{h,0} + \sum_{s} \gamma_{s,h} \cdot z_{s,n} + \psi_{h,n} \tag{4}$$

where $z_{s,n}$ represents the generic s^{th} individual characteristic of the respondent n, $\gamma_{h,0}, \gamma_{s,h}$ represent coefficients to be estimated and, finally, $\psi_{h,n} \sim N(0, \sigma_{\psi_h})$ represents the individual random error term of the latent factor h, assumed as normally distributed with 0-mean and standard deviation σ_{ψ_h} to be estimated on the data.

The latent factors are indirectly measured by the attitudinal responses in the Likert scale. The measurement equation model defines the relationship between the latent factors $LF_{h,n}$ and the generic q^{th} attitudinal indicator $I_{q,n}$ for the individual n, i.e. the Likert score indicated in the responses, as:

$$I_{q,n} = \sum_{h} \zeta_{q,h} \cdot LF_{h,n} + \xi_{q,n} \tag{5}$$

where $\zeta_{q,h}$ represent the coefficients of the latent factor $LF_{h,n}$ in the q^{th} indicator, while $\xi_{q,n} \sim N\left(0, \sigma_{\xi_q}\right)$ is the individual specific random term as normally distributed with 0-mean and standard deviation σ_{ξ_q} to be estimated on the data. Under such assumption, the probability that the indicator $I_{n,q}$ faced by the individual n for the attitudinal statement q is equal to a value r is given by a normal probability density function (PDF), whose parameters need to be estimated on real data.

Joint estimation of the HCM) The model is estimated through the joint maximum simulated log-likelihood (*SLL*) method, where coefficients of both choice and latent variable models are simultaneously estimated. For the sake of brevity, we do not include the explicit formulation of the SLL. Although handling a joint SLL is cumbersome from a computation standpoint, it eases the identification of parameters and avoids a loss of asymptotic efficiency of the estimates occurring in the sequential estimation case (see Abou-Zeid and Ben-Akiva, 2014; § 2.4). Note that the HCM assumptions above described imply a conditional independence between choices and attitudinal responses. i.e. choices do not depend upon attitudinal responses and vice versa. We assume that this is justifiable within the analysed context, as stated choices have been presented before the attitudinal statements during the survey, and attitudinal statements do not include statements on the comparison between the two proposed options.

Treatment for sample bias) To overcome the sample bias limitations, we weighted each individual likelihood within the SLL according to weights that considered the actual share in the population for gender, age, occupation type and education level. In particular, each individual n has been assigned with a weight computed as $w_{n|category} = p_{population}(\text{category}_n)/\ p_{sample}(\text{category}_n)$, where the term at the numerator indicates the share of the category (e.g. female, under 25, high education and employed) within the population (from official census statistics) and the share of the same category within the sample. Each category corresponds to the product of the segment shares reported in Table 3.

6. Results and discussion

6.1. Exploratory factor analysis (EFA)

In the analysis of the attitudinal responses on the 5-point Likert scale, we discarded some attitudinal statements by the successive analysis after noticing a low internal consistency of some groups of statements and the non-significant impact on choices revealed by the estimation of the HCM. In particular, we discarded the indicators I_1, I_2, I_3, I_8 and I_9, leading to a total of 10 indicators in the final analysis.

To extract the main latent factors explaining the variance of the attitudinal responses to the remaining 10 indicators, we performed an orthogonal Exploratory Factor Analysis (EFA) with Varimax rotation, with factor loadings estimated through maximum log-likelihood. Preliminarily, we verified the suitability of the EFA on our data, through Bartlett's sphericity test (Bartlett, 1937), which allows us to assess that the correlation matrix of the attitudinal responses is significantly different from the identity matrix. In other words, we aim to test whether there are strong correlations between items so that a dimension reduction is suitable. The test provided a null p-value and a $\chi^2 = 850.92$, far greater than the χ^2 threshold with 45 degrees of freedom (=61.66). Furthermore, we conducted the Kaiser-Olkin-Meyer (*KMO*; Kaiser, 1970) test, which measures the proportion of variance of each item that represents a common share of variance, obtaining a Measure of Sampling Accuracy (*MSA*) equal to 0.69, which can be considered as acceptable for conducting an EFA.

We implemented the EFA to assess the main latent factors influencing the attitudinal responses. To implement the EFA, we resorted to both Matlab and RStudio routines, contrasting the results to assess their equivalence. The results on the final sub-set of indicators are shown in Table 4, where also Cronbach's α (Cronbach, 1951) and the relative importance index (*RII*) of the statements have been reported. The values of the loading factors below a threshold of 0.5 have been blanked, to improve the interpretability of the results.

To determine the minimum number of factors to be extracted, we considered several criteria, including the eigenvalue analysis, resulting in a minimum number of eigenvalues greater than unity equal to 3, with an elbow in the eigenvalue bar graph between 2 and 4. As shown in Table 4, with 3 latent factors the share of the total variance explained is 44 %. Since the goal of EFA is to inform the subsequent implementation of an HCM, it is good to preserve the latter from excessive complexity compared to the available data and, therefore, after a trial-and-error among many HCM specifications, we obtained that working with the 3 latent factors shown in Table 4 was the best option. Furthermore, the addition of a fourth latent factor in the EFA leads to a total amount of variance explained to 45 %, i.e. a very marginal improvement with reference to the analysed case, and a less-clear interpretation of the latent factors extracted. The resulting EFA with 3 latent factors has a nearly null p-value and a $\chi^2 = 514.4$, which is well above the threshold value with 18 degrees of freedom (=28.9), which testifies that 3 latent factors are sufficient to explain the variability in the data.

As evident from Table 4, the first latent factor, accounting for 18.3 % of the total variance, is measured significantly by the indicators I_4, I_5, I_6 and I_7, which are statements related to the concern for the pandemic. The value of Cronbach's α (0.76) reveals a good internal consistency, i.e. the four indicators measure the same underlying latent construct. The second latent factor explains the 13.3 % of the total variance and is measured by the indicators I_{12}, I_{14} and I_{15}, and has been interpreted as trust in city services, also showing a very good internal consistency (0.79). The third factor explains the 12.4 % of the total variance and is mainly measured by the indicators I_{10}, I_{11} and I_{13}, which are the statements related to the degree of (dis)trust in national government initiatives. The internal consistency of such indicators is lower as Cronbach's α is equal to 0.55, but still acceptable to conduct the successive analyses. for similar considerations). Finally, the RII measure reveals that I_7 and I_{13} are the most important relative statements within the proposed questionnaire (RII > 0.9).

Indeed, notice that Cronbach's α assesses only the measurement part of the latent variable model, thus not relating the attitudinal answers to the socio-demographic characteristics, which are introduced in the structural equations of the HCM (see also Kim et al., 2014)

6.2. Hybrid choice model

This section shows the results of the HCM estimation. Preliminarily to the analysis, we reported the shares of stated choices for the two alternatives and the opt-out one in the three pandemic scenarios. The shares are reported in Fig. 3. As can be seen, there is a significant difference in observed shares of stated choices across the three hypothetical pandemic alert situations. Indeed, while no substantial difference is observed between low and moderate pandemic situations, the difference becomes significant in the high pandemic alert scenario, where the opt-out alternative has the highest market share.

In the following, we report the details about both the utility and latent variable models.

Utility specification) In the following, the attributes will be indicated as: *PR* = price of the ticket per single trip, *OR* = allowed occupancy rate on board [%], *DF* = disinfection frequency [time per day], *GA* = gel availability, *AF* = air exchange/filtering, *GP* = green pass check at the entrance, *PC* = pandemic concern, *TCS* = trust in city services, *DNG* = distrust in national government initiatives.

The utility coefficients have been finally characterized as:

Table 4
Exploratory factor analysis (EFA) – loading factors, explained variance and latent factors labelling. NOTE: In the computation of Cronbach's α the reverse scoring has been applied, inverting the 5-point Likert scale where sentences have been framed with a different score order.

Indicator	Exploratory factor analysis (EFA) with 3 attitudes (threshold = 0.5)	Latent factor 1	Latent factor 2	Latent factor 3	RII
I_4	*I keep updated on the trend of the pandemic (number of new infections, deaths, occupancy of intensive care units, etc.) and vaccines.*	0.755	–	–	0.726
I_5	*I strictly observe safety measures related to Covid −19 emergency (e.g., mask use, hand sanitization, social distancing).*	0.924	–	–	0.849
I_6	*It bothers me to share a means of transportation with other travelers.*	0.535	–	–	0.535
I_7	*I feel I have a duty to myself and others to adopt congruent behavior so as to contain the spread of the Covid-19 virus.*	0.814	–	–	0.920
I_{10}	*I believe that the current Italian government is not effectively handling the emergency situation of the Covid-19 pandemic.*	–	–	0.691	0.627
I_{11}	*In the past, I have been disappointed with the management choices of sensitive situations by institutions.*	–	–	0.902	0.755
I_{12}	*I believe that the Campania Region and the City of Naples are constantly working for the enhancement of the Naples Metropolitan City.*	–	0.667	–	0.407
I_{13}	*I believe that PT in the Naples Metropolitan City is not up to European standards.*	–	–	0.566	0.925
I_{14}	*The state of local public transportation in the Naples Metropolitan City has improved over the past few years.*	–	0.792	–	0.459
I_{15}	*I am satisfied, in general, with the public services in the City of Naples.*	–	0.882	–	0.344
	Labelling	**COVID-19**	**City services**	**National government**	
	SS loadings	2.738	2.002	1.859	
	Explained variance	18.3 %	13.3 %	12.4 %	
	Cumulative explained variance	18.3 %	31.6 %	44.0 %	
	Cronbach α	0.759	0.788	0.549	

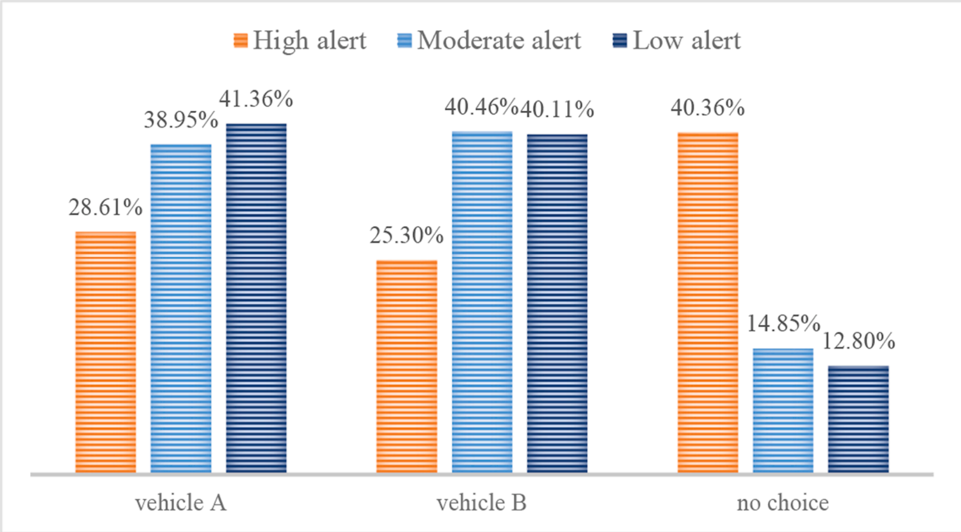


Fig. 3. Observed shares of stated choices in the analysed sample for all pandemic alerts.

$$\beta^{*}_{PR,n} = \beta_{PR} \cdot att_{PR,n} \tag{6a}$$

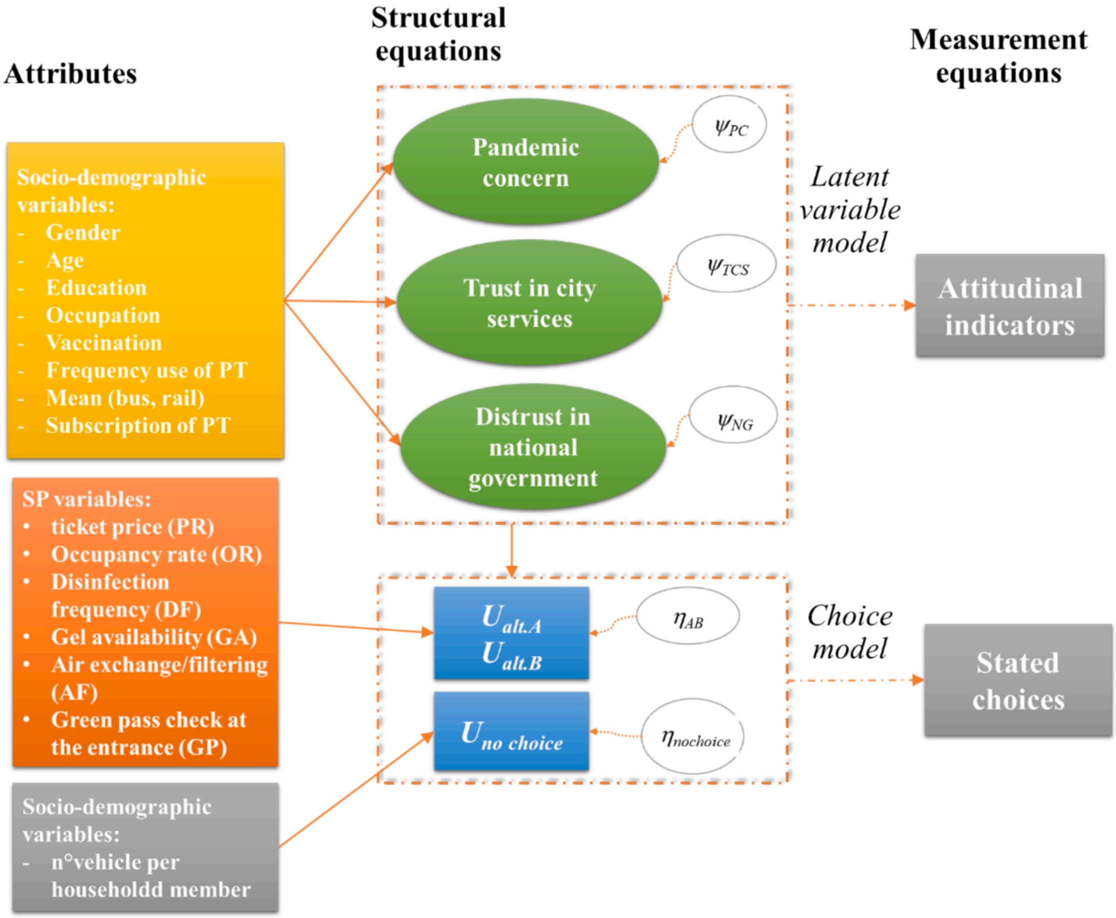


Fig. 4. HCM framework.

$$WTP^{*}_{OR,n} = \left(WTP_{OR,L} \cdot L_{n,t} + WTP_{OR,M} \cdot M_{n,t} + WTP_{OR,H} \cdot H_{n,t} + \lambda_{PC,OR} \cdot PandemicConcern_n + + \lambda_{TCS,OR} \cdot TrustCityServices_n\right) \cdot att_{OR,n} \tag{6b}$$

$$WTP^{*}_{DF,n} = \left(WTP_{DF,L} \cdot L_{n,t} + WTP_{DF,M} \cdot M_{n,t} + WTP_{DF,H} \cdot H_{n,t}\right) \cdot att_{DF,n} \tag{6c}$$

$$WTP^{*}_{GA,n} = WTP_{GA} \cdot att_{GA,n} \tag{6d}$$

$$WTP^{*}_{AF,n} = \left(WTP_{AF,L} \cdot L_{n,t} + WTP_{AF,M} \cdot M_{n,t} + WTP_{AF,H} \cdot H_{n,t}\right) \cdot att_{AF,n} \tag{6e}$$

$$WTP^{*}_{GP,n} = \left(WTP_{GP,L} \cdot L_{n,t} + WTP_{GP,M} \cdot M_{n,t} + WTP_{GP,H} \cdot H_{n,t} + + \lambda_{DNG,GP} \cdot DistrustNationalGovernment_n\right) \cdot att_{GP,n} \tag{6f}$$

where $att_{k,n}$ represents a dummy variable obtained by the ex-post questions on the SP processing strategy of the respondent (see Section 4.1), with value $= 1$ if the respondent n has declared the attendance of the attribute k, 0 otherwise, while PC_n, TCS_n and DNG_n indicate the pandemic concern, trust in city services and distrust in national government for the individual n, respectively. The general structure in (6a)-(6f) allows a variation of almost all the coefficients across the three hypothetical pandemic alert situations, except for gel availability, which has proved not to vary significantly across pandemic alert situations during the trial-and-error process. Price coefficient has been kept fixed across scenarios, to give a common parameter to all pandemic alert observations, while gel availability and air exchange/filtering coefficients were restricted to be equal across all and two out of three of the pandemic alert scenarios, respectively, for statistical significance reasons (see Section 6.2). The alternative specific constant (ASCs) of the opt-out alternative interacts with the variable indicating the number of vehicles per household member.

Latent variable model specification) The structural equations of each latent factor have been specified as a function of several socio-demographic, household characteristics and mobility habits of each respondent. The measurement equation model has been specified as consistent with the EFA results in Table 4. A representation of the modelling framework used in the current analysis has been reported in Fig. 4. In particular, to normalize the model, one coefficient per each latent factor in the measurement equation model has been normalized to 1 to set the scale of the model (Abou-Zeid and Ben-Akiva, 2014). In the current analysis, the normalized coefficients are those of the attitudinal indicators I_5, I_{11} and I_{15}.

Table 5
HCM results/choice model component.

Name	Estimate	*t*-test
Alternative specific constants		
alternative specific constant on the opt-out (high pandemic) $\beta_{nochoice,H}$	−1.861	*−5.83*
alternative specific constant on the opt-out (moderate pandemic) $\beta_{nochoice,M}$	−3.888	*−11.77*
alternative specific constant on the opt-out (low pandemic) $\beta_{nochoice,L}$	−3.622	*−11.00*
# of vehicles per household member on opt-out (shift) $\beta_{nochoice,n^{\circ}vehicles\_per\_household}$	1.654	*4.89*
Level-of-service (LoS)		
price (β_{PR})	−1.168	*−6.99*
occupancy rate (high pandemic) $WTP_{OR,H}$	0.012	*6.40*
occupancy rate (moderate pandemic) $WTP_{OR,M}$	0.005	*3.69*
occupancy rate (low pandemic) $WTP_{OR,L}$	−0.010	*−4.37*
disinfection frequency (high pandemic) $WTP_{DF,H}$	−0.331	*−5.56*
disinfection frequency (moderate pandemic) $WTP_{DF,M}$	−0.225	*−5.20*
disinfection frequency (low pandemic) $WTP_{DF,L}$	−0.041	*−1.34*
gel availability WTP_{GA}	−0.051	*−1.57*
air exchange/filtering (high pandemic) $WTP_{AF,H}$	−0.394	*−5.80*
air exchange/filtering (moderate pandemic) $WTP_{AF,M}$	−0.394	*−5.80*
air exchange/filtering (low pandemic) $WTP_{AF,L}$	−0.301	*−4.61*
green pass check at the entrance (high pandemic) $WTP_{GP,H}$	−0.363	*−4.48*
green pass check at the entrance (moderate pandemic) $WTP_{GP,M}$	−0.191	*−3.34*
green pass check at the entrance (low pandemic) $WTP_{GP,L}$	0.001	*0.02*
Error components		
opt-out $\eta_{nochoice}$ standard deviation	−2.685	*−17.33*
nest AB η_{AB} standard deviation	0.511	*2.52*
Latent variable coefficients		
Pandemic concern in occupancy rate $\lambda_{PC,OR}$	0.013	*5.77*
Trust in city services in occupancy rate $\lambda_{TCS,OR}$	0.002	*2.00*
Distrust in national Government initiatives in green pass check at the entrance $\lambda_{DNG,GP}$	−0.095	*−1.33*
# individuals	313	
# choice observations	5634	
# par. choice model	32	
LL(0)	−6189.58	
LL (choice model)	−5028.36	
ρ2	0.188	

Choice model results) The results of the choice model component are reported in Table 5. The final specification has been obtained through a trial-and-error process. For the analysis, it is interesting to show all the LoS variable coefficients, also when not significantly different from the null value, while we constrained each coefficient to have an equal value across pandemic alert in two cases: gel availability (unique value) and air exchange/filtering (equal value across low and moderate pandemic alert). To assess the difference in coefficient values across different pandemic alert scenarios, t-tests for differences across coefficients have been performed, retaining only those coefficients who are different across pandemic scenarios. For the sake of brevity, we do not show such tests in the paper. In terms of interaction effects, instead, only significant interactions between ASCs and socio-demographic and travel habits variables have been retained. This allows us to better interpret the importance of each LoS attribute when varying the pandemic alert situation, which is the main purpose of the current analysis while simplifying the model in terms of interaction effects.

ASCs of the opt-out alternative have been differentiated in the three pandemic alerts, to be able to reproduce the different observed market shares (Ben-Akiva and Lerman, 1985) in each pandemic scenario. Note that also the ASCs for the two travel options have been tested, to capture the left–right bias effect, but since no significant difference has been found between the two, we prefer to set the latter to 0 and to estimate the opt-out ASCs. No significant interactions between ASC and socio-demographic characteristics have been found for the two travel option alternatives, while the number of vehicles per household member significantly interacts with the ASC of the opt-out alternative. The price coefficient is negative and significant, as expected. The first noticeable result of the analysis is observed in WTPs for allowed occupancy rate on board, which is different in sign between the pandemic alert scenarios. In particular, looking at the two extreme pandemic alert scenarios, PT users are willing to pay for having more allowed capacity on board in low pandemic conditions, while they are willing to pay for less allowed capacity on board in high pandemic conditions. This may be explained by the fact that PT users desire regular travel conditions in a low pandemic alert, i.e. without restrictions, while they feel safer in high pandemic conditions when restricting the onboard capacity. In this regard, it is important to note that reductions in the occupancy rate when the pandemic alert is low could be perceived as a potential increase in waiting times, thus travellers would be willing to accept monetary compensation. The value of WTP in the moderate pandemic alert situation has the same sign as that of the high pandemic alert situation but it is less significant in value. For example, PT users of the sample are willing to spend about 1.20 euro cents for a 1 % reduction in onboard capacity, i.e. about 0.60 euro for a 50 % reduction in onboard capacity in case of high pandemic alert scenario.

The WTP for disinfection frequency is much higher in the moderate and high pandemic alert scenarios, while much less significant in the low pandemic alert scenario. Concerning the gel availability on board, it results that PT users are willing to spend a very little amount to have the gel on board (about 5 euro cents more). Air exchange/filtering is a significant attribute the users considered in their stated choices, with a fairly high WTP in all the scenarios, although higher for moderate and high pandemic ones. Finally, the WTP for the green pass check at the vehicle entrance is not significant and has a positive sign (i.e. people would be willing to spend not to have it) in low pandemic scenarios, while significant and negative (i.e. users would be willing to spend to have it) in the moderate/high pandemic alert scenarios. This may be due to the consideration that a preventive check at the entrance would be perceived as an improved safety strategy in high and moderate pandemic alert scenarios, so users are willing to spend more to have it, while the fact that it leads to a higher ascent time to access the vehicle is considered an undesirable characteristic in low pandemic alert scenarios, where users prefer more regular travel conditions.

Both the nesting and opt-out error components are highly significant, testifying both significant correlations amongst the utilities of the travel options and a significant panel effect across the same choice observations of each respondent.

Regarding the utility coefficients of the latent factors, we found significant interactions between pandemic concern and occupancy rate, trust in city services and occupancy rate as well as distrust in national government initiatives and green pass check at the entrance. In particular, the relative coefficients of the interactions of the latent factors and the occupancy rate are positive, implying an increase of WTP for such onboard characteristics as the pandemic concern rises. This aspect will be further discussed in Section 7.1. Similarly, people who are more trustful/satisfied with city services tend to be more willing to spend to reduce occupancy rates too. In contrast, users who are dissatisfied with national government management of recent sensitive situations are less willing to spend for having the green pass check at the entrance, testifying that a general distrust in government initiatives is reflected in the preference for one of its monitoring tools. No significant interactions have been found between the analysed latent factors and gel availability on board and air exchange/filtering.

Goodness of fit) The choice model exhibits reasonable goodness of fit, with a rho square value of 0.188 as reported in Table 5. WTP values are important for designing services and configuring pricing schemes, so we reported the confidence intervals of the WTP estimates at 95 % in Table 6. Note that Table 6 reports only the confidence intervals for the base WTP values, i.e. without considering the interaction between attributes and latent factors in (6*b*) and (6*f*). In general, this allows for assessing the robustness of the estimates

Table 6
Willingness to pay for onboard vehicle characteristics: 95% confidence intervals.

	high pandemic			moderate pandemic			low pandemic		
characteristic	**Estimate**	**lb**	**ub**	**Estimate**	**lb**	**ub**	**Estimate**	**lb**	**ub**
occupancy rate (1 % less)	0.01 €	0.01 €	0.02 €	0.00	0.00 €	0.01 €	−0.01 €	−0.01 €	−0.01 €
disinfection frequency (1 time more per day)	0.33 €	0.21 €	0.45 €	0.22	0.14 €	0.31 €	0.04 €	−0.02 €	0.10 €
gel availability	0.05 €	−0.01 €	0.12 €	0.05	−0.01 €	0.12 €	0.05 €	−0.01 €	0.12 €
air exchange/filtering	0.39 €	0.26 €	0.53 €	0.39	0.26 €	0.53 €	0.30 €	0.17 €	0.43 €
green pass check at the entrance	0.36 €	0.20 €	0.52 €	0.19	0.08 €	0.30 €	0.00 €	−0.10 €	0.10 €

to the estimation sample. We observe that estimates are generally robust, except for the gel availability case and the disinfection frequency in the low pandemic alert scenario, which is a result closely related to the t-ratio values reported in Table 5 for the same coefficient estimates. Note that WTP for the occupancy rate can also be expressed in terms of seats rather than a percentage. In particular, considering the high pandemic scenario, under the assumption that the passenger's bus capacity is 80 passengers/bus and 20 seats/bus, the WTP is about 1.50 euro cents for having one less passenger (seated or not) on board and 6 euro cents for having one less seat allowed on board. The same can be obtained for trains, by considering 200 total passengers/wagon, thus obtaining a WTP of about 0.6 euro cents for having one less passenger (seated or not) on board in the wagon.

Relative importance of attributes) As WTPs refer to different measure units, it is useful to compare the relative importance of each characteristic in their whole variation range, i.e. the total range of attribute values proposed in the SP survey. For this purpose, we assessed the importance of each characteristic, by computing the relative importance of attributes (see e.g. Merkert et al., 2022), through the percentage contribution of the total range variation of each attribute to the utilities of the two unlabelled travel options *A* and *B*. The results have been reported in Fig. 5 for each pandemic alert situation. As can be seen, the price is always the main service characteristic considered in users' choices. In terms of safety characteristics, the ranking of importance changes as a function of the pandemic alert scenario. In particular, the disinfection frequency is the most important attribute in moderate and high pandemic situations, while the occupancy rate is the most important one in low pandemic situations. Air exchange/filtering assumes significant relative importance in utilities in all the pandemic situations, while the green pass check at the vehicle entrance increases its importance as the pandemic situation worsens. Notice that occupancy rate has similar relative importance in low and high pandemic scenarios, although with different signs, not captured in the relative importance analysis, which depends just upon the absolute values of the contribution to the utilities. Notice also that, although the coefficients for the air exchange/filtering are equal in moderate and high pandemic scenarios, its relative importance is higher in the moderate scenario, because of the reduction in importance of other attributes (occupancy rate, disinfection frequency and green pass check). As observed also in WTP values, the gel availability on board turns out to be the relatively least important attribute in explaining the sample's stated choices. This finding is similar to the results by Chen et al. (2022), who found no significant marginal utility in providing hand rubs. The results of this analysis provide important guidance for the companies operating PT in the city because there are safety measures that represent ad hoc expenditure items for the company, while others potentially do not. For instance, people perceive a green pass check at the entrance as much more important, and the one can be managed by the personnel staff onboard, without further costs, while, for instance, providing hand sanitizers on board does require an expenditure, but with a very marginal increase in the perceived utility of users. The management of other safety measures represents a delicate point. For instance, providing new air filtering systems for air recirculation and bacteria/viruses deletion on board, as well as increasing the disinfection frequency on board requires ad hoc economic plans or special subsidies. Furthermore, the reduction of the capacity on board can represent just an apparent cost-free safety measure. Indeed, reducing the capacity may have repercussions on the level of fulfilment of the demand, thus implying a needed increase in the frequency of the service. This consideration forms the basis for the simulation exercises presented in Section 7.2, where we investigated the possibility of increasing the allowed occupancy rate on board in higher alert periods, so as not to fall into the condition for which a required higher frequency (thus costs) to satisfy the demand is required. Notice also that the considered safety measures pose equity issues, as potential iniquities could be generated for some disadvantaged groups in the population, an issue that will be discussed in Section 7.4.

Latent variable model results) The results for the latent variable model are reported in Table 7 (structural equations model) and Table 8 (measurement equations model). As can be observed, there is a significant correlation between some respondents 'categories

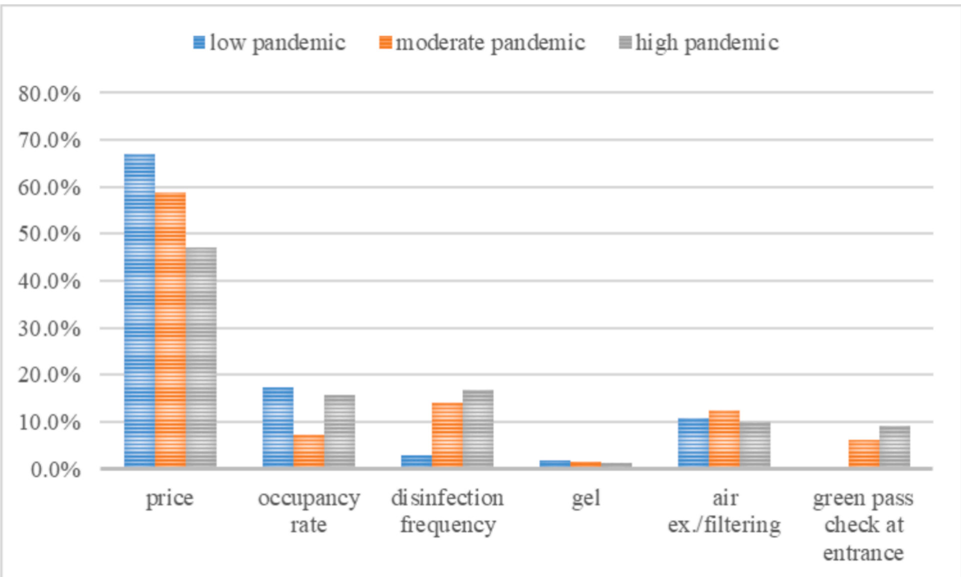


Fig. 5. HCM results /relative importance of attributes.

and the three analysed latent factors. In particular, younger users (under 25 and 26–35) are significantly less concerned with the pandemic, while people with a complete vaccination are correlated with higher responses in relative indicators. This latter aspect is important also for discussing some further policy implications in Section 7.3. Indeed, at the time of the survey, the vaccines were implemented for a year and a half, having the population had all the time to have its first two doses and even the complete vaccination cycle, as shown in Section 4.2. Therefore, non-vaccinated at the time of the survey were likely to be reluctant to the vaccination technology or less concerned about the pandemic, in general. In this sense, vaccinated people also tend to be more sensitive to the pandemic topic in general and to agree more with the answers to the concerned statements (i.e. 4, 5, 6 and 7). In terms of trust in city services, highly educated people and non-regular PT users are more satisfied with city services. In terms of distrust in the national government, people in the age range 26–50 tend to have less trust (positive coefficients), while highly-educated, completely vaccinated people and non-regular PT users have less distrust (negative coefficients) in national government initiatives. Other variables, such as income and travel purpose have been tested in the analysis but found to be non-significant neither in the choice model nor in the structural equation model. For what concerns the income, it is worth highlighting two aspects. The first refers to the presence of 25.9 % in the sample indicating the preference not to declare it, thus introducing a noise in the collected responses about this aspect. The second refers to the fact that respondents indicated their preferred option for ticket subscription before the SP survey. According to the ticket systems in the city, as shown in Table 1, there are subscription options that include discounts for users with a value of the Equivalent Economic Situation Indicator (ISEE in the Italian legislation) of the household below a certain threshold. As this information has been considered in the preliminary question used to direct the presentation of the set of SP scenarios, it can be concluded that the effect of the variation in the income has been significantly absorbed in setting the proper price level within the SP scenarios, thus reducing the effect of the income in the variation of sensitivities (e.g. price or WTPs) of respondents.

The results of the measurement equation model coefficients confirm the structure suggested by the EFA in Section 6.1, with all latent factors coefficients and all the standard deviations being significant at a 95 % threshold. In other words, latent factors are significantly measured by the groups of indicators previously detected in the EFA.

6.3. Comparison with other studies in the literature

The results shown in Section 6.2 can be discussed in view of previous findings in the literature, according to various aspects.

Pandemic alert scenarios) There are some studies in the literature introducing the pandemic alert as a context variable. As anticipated in Section 2.2, Chen et al. (2022) performed a SP on mode choice, introducing different pandemic alert scenarios (called medium, high and very high), on data collected in the period February 2020 – January 2021 in the Netherlands. They treated the pandemic scenarios as dummy variables interacting with the option not to travel in their mode choice experiment, finding that the utility of the opt-out option increased when increasing the pandemic alert. Pollock et al. (2024) analysed the mode choice and value of crowding (*VoC*) in Canada, considering different risk scenarios (low, moderate and high, as in the current study). Also in that case, the utility of each of the considered travel modes increased when decreasing the perceived risk within the scenarios. The effect of policy aimed at restricting mobility conditions has been introduced also by Pan et al. (2023), who found that willingness to stay in the city during the Chinese Spring Festival depends on the stay-in-place policy measures and the collective behaviour manifested on social networks.

The results presented in the current paper, although referred to a period where vaccines were highly penetrated in the population, confirm that the pandemic entity plays a role in explaining the opt-out choices. Notice that the above studies introduced the pandemic alert and the latent factors in the model as dummy variables within the ASCs, i.e. not interacting directly with the ticket price, so their WTPs are equal across pandemic contexts, while the current study has differentiated the WTP estimates by pandemic scenario (see the concerned discussion in Section 7.1).

Capacity of the vehicles) Since the first studies on the pandemic, researchers substantially agreed that social distancing decreases the risk of infection due to exhaled droplets. This has also been confirmed by studies considering virus transmission models (see e.g. Sun and Zhai, 2020). In the early stages of the pandemic, Kumar et al. (2021) found that the risk of infection was way lower if reducing the allowed occupancy to just 15 passengers on buses. Awad-Núñez et al. (2021a) found that an increased supply to avoid crowding was

Table 7
HCM results / latent variable model component – structural equation model.

	Pandemic concern		Trust in city services		Distrust in national government	
	Estimate	*t*-test (0)	Estimate	*t*-test (0)	Estimate	*t*-test (0)
Intercept	0.493	*2.64*	−0.186	*−0.97*	0.401	*1.78*
Male	−0.359	*−3.94*	0.016	*0.17*	−0.136	*−1.36*
Age under 25	−0.816	*−5.38*	0.199	*1.19*	0.070	*0.39*
Age 26–35	−0.718	*−5.37*	−0.002	*−0.01*	0.490	*2.99*
Age 36–50	−0.367	*−2.10*	−0.124	*−0.69*	0.419	*2.25*
High education	0.229	*2.08*	0.208	*1.86*	−0.271	*−2.33*
Complete vaccination	0.241	*2.02*	−0.118	*−0.98*	−0.308	*−2.12*
PT subscriber	0.073	*2.79*	−0.079	*−0.84*	−0.105	*−1.06*
Bus	0.051	*0.57*	0.058	*0.64*	0.197	*1.93*
Non-regular PT user	−0.239	*−2.61*	0.244	*2.57*	−0.392	*−3.56*
standard deviation	0.764	*13.61*	0.788	*16.45*	0.708	*8.82*

Table 8
HCM results / latent variable model component – measurement equation model.

	Pandemic fear		Trust in city services		Distrust in national government		Standard deviation	
Indicator	Estimate	*t*-test (0)	Estimate	*t*-test (0)	Estimate	*t*-test (0)	Estimate	*t*-test (0)
I_4	1.12	*11.58*	–	–	–	–	0.92	*19.90*
I_5	1.00	–	–	–	–	–	0.62	*14.37*
I_6	0.72	*7.31*	–	–	–	–	1.14	*23.66*
I_7	0.70	*12.31*	–	–	–	–	0.57	*19.71*
I_{10}	–	–	–	–	1.07	*6.80*	0.84	*13.71*
I_{11}	–	–	–	–	1.00	–	0.83	*14.29*
I_{12}	–	–	0.83	*10.71*	–	–	0.82	*21.83*
I_{13}	–	–	–	–	0.28	*3.30*	0.87	*24.27*
I_{14}	–	–	1.11	*11.96*	–	–	0.77	*16.92*
I_{15}	–	–	1.00	–	–	–	0.48	*11.31*

the most important factors for PT users to preserve their wiling to use PT during the pandemic. Chen et al. (2022) found a significant marginal utility for the bus option only for the case of an allowed occupancy rate on board equal to 25 % w.r.t. a 100 % base scenario. Computing their WTP values, it results a value for the WTP of about half euro for having a reduction to 25 % of allowed capacity on board. Notice that, as emphasized in the previous excerpt, this is not directly comparable with our results, because we differentiated the WTP values for each pandemic alert scenario. An equivalent situation in our case study would lead 1.50 euro more or less to restrict capacity in high/low pandemic scenarios, respectively, with a much less significant WTP in the case of a moderate alert. Bwambale et al. (2023) conducted an unlabelled choice experiment in Uganda and Bangladesh, investigating PT and paratransit users' preferences for safety measures on board. They considered the effect of the implementation or not of a half capacity allowed on board, finding a higher WTP for the latter option for users making trips with children w.r.t. to users without children, in both Uganda and Bangladesh. In particular, they estimated an average WTP of 1.32 USD in Uganda for having a 50 % capacity on board, which resembles our findings, and 0.43 USD in Bangladesh.

There are also plenty of studies discussing the problem of capacity in relation to the real-time crowding on board, aiming at assessing the value of travel time savings (VTTs) crowding multipliers (see the discussion of Section 7.4). However, this study differs from all the studies dealing with the VoC assessment, as it does not investigate the demand problem, but rather the sensitivity and WTP for safety measures on board, being real-time information service on onboard crowding not available in the city of Naples. Furthermore, the problem of the restricted capacity has been discussed also for other specific modes, such as air travel (e.g. Singh et al., 2023b) or customized bus services (He et al., 2023).

Hygiene and cleanliness of vehicles) Information on the disinfection of PT vehicles has been deemed as a key determinant of users' behaviour since the early stages of the pandemic (see Arunwuttipong et al., 2021). Disinfection and hygiene of spaces are found to be significant in the current study, confirming results from other works, such as Awad-Núñez et al. (2021a), Beck et al. (2021), Basnak et al. (2022) and Chen et al. (2022). In particular, Chen et al. (2022) found that the most significant level of disinfection frequency is once per 8 journeys, more than the attribute levels corresponding to once a day, once per 4 journeys and once per each journey (not significant). Pollock et al. (2024) surprisingly (in the words of the same authors) found that daily cleaning of vehicles did not significantly impact the propensity to use the PT in Calgary (Canada), while the converse resulted in Basnak et al. (2022) in Chile, who analysed it as the time between disinfections. Liu et al. (2023), in comparing the data between 2020 and 2021 in Toronto (Canada), introduced the effect of the disinfection of vehicles at the end of the day, but did not consider it in their final analysis, more focused on the methodological comparison between the HCML and deep neural networks. Bwambale et al. (2023) considered the effect of the implementation or not of daily disinfection on board, finding that the WTP for implementing disinfection is higher for PT users making trips with children in Uganda w.r.t. users without children, in both geographical contexts (Uganda and Bangladesh). Their estimated WTP was 0.37 USD for having disinfection on board in Uganda, which resembles our results, and 0.10 USD in Bangladesh. Chen et al. (2023) considered the time between disinfections on board in their analysis in Hong Kong, finding that it was negative and significant, leading to a positive modal shift towards the bus (+1.05 %) in a forecasting scenario with the implementation of a double disinfection frequency w.r.t. to the base scenario. Disinfection has been also considered in other contexts, such as Singh et al. (2023b) for the air transport case, who found a significant preference towards luggage sanitation for both classes of Indian air transport users considered in their latent class model.

Results provide clear indications for PT providers in the city. In particular, the awareness of the disinfection of the vehicles is found to be significant in our models and increasing with the entity of the pandemic alert. This poses questions about the strategies to be implemented so as not to impact the service frequency, as the disinfection requires time and can lead to increased cycle time of buses/trains. Of course, the most suitable moment to disinfect vehicles without risk of overcrowding is during the off-peak hours, when the PT providers usually reduce the service frequency.

Air quality on board) As reported in the bibliometric analysis by Sharifi (2022), air quality is, in its general meaning, the most dominant topic in COVID-19 related literature. The importance of the air change and ventilation has been advocated in early pandemic studies on PT (see Shen et al., 2020). The presence of air change and ventilation on board vehicles has been investigated by many authors, also though the use of virus transmission models (see e.g. Sun and Zhai, 2020; Zhou and Koutsopoulos, 2021). Yap et al. (2023) argued that buses might be perceived as better than metro in terms of risk of COVID-19 infections, due to the greater ventilation, because of the possibility for passengers to open windows. Iglesias and Raveau (2024), in their analysis of mode choice in

Santiago (Chile), in considering the crowdedness aversion in PT, concluded by their HCM application that informing people of cleanliness and ventilation of vehicles would avoid migration of PT users towards other travel modes. Chen et al. (2023) indicated the air exchange rate of the compartment of vehicles as one of the proactive measures, but found that Hong Kong users of their sample were unaware of the in-vehicle air quality. Xu et al. (2024) considered the information about ventilation on board as characterizing their SP variable "perceived route epidemic risk", expressed in percentage terms, finding that users of rail transit are more likely to change route if information displayed on board indicates a deterioration of the ventilation on that route.

In general, the results of the current paper should be looked at with the right perspective. The principle of this study is that people who are aware of safety measures onboard can be willing to pay more/less for certain safety measures. Thus, the point of this study, realised in collaboration with Azienda Napoletana per la Mobilità (i.e. the main PT provider of the city), is that of investigating how people would react to information about safety measures on board. Our analysis is explorative in this sense and aims to understand which is the reaction of PT users to the information on the air quality on board. Thus, it can be concluded that, when aware of them, PT users of the sample exhibit higher WTP for having better air quality on board, if aware of the systems on board. This implies that marketing campaigns aimed at advertising the air quality on board and the cleanliness of vehicles would have a positive impact on the propensity of the users in the city, and, most importantly, the information about the air quality on board may play a crucial role in determining users' WTPs.

Vaccine certification) In general, the concern for detection of people that could lead to an increased risk of exposure was an argument treated in the earlier literature on the pandemic. For instance, Awad-Núñez et al. (2021a) assessed the importance that Spanish PT users attached the eventual policy action for which only non-infected people could have used the PT, but found it much less important than the other aspects mentioned above. The Green Pass certification is a particular tool introduced by the Italian government to register the personnel vaccination status of individuals, eventually precluding the access to certain facilities. A study considering the mandatory certification for the vaccination is the already cited one by Singh et al. (2023b), in the air travel context. In their analysis of 2022 data, they found that vaccinated Indian air travellers prefer the mandatory vaccine certification over a molecular test, while the converse applies to non-vaccinated travellers. In their analysis of preferences for public health policies, Yang et al. (2024), analysing data from a questionnaire collected in 2022, found that Chinese people have a positive propensity to a universal mandatory booster vaccination policy, while a negative propensity for non-vaccinating or vaccinating just high-risk groups. In this sense, results for our sample confirm the positive base propensity to green pass certifications, as they are associated with safer trips and reduced risk of infection in the user's perception.

Impact of vaccination) Several studies tried to introduce the impact of the introduction of the vaccination technology before it was implemented, or at least not on a large scale. For instance, the vaccine penetration in the reference country was introduced as an SP variable in DCEs by Bansal et al. (2022) in their VoC study in London, finding that the hypothetical vaccine penetration positively impacted the utility of taking an alternative, while decreasing its positive effect when the crowding increased. The studies by Singh et al. (2023a) for the VoC in the Netherlands and Loa and Habib (2023) in a mode choice experiment in Canada treated the vaccination status as a context variable. In both cases, the analyses had data from spring and summer 2021, respectively, i.e. when vaccine penetration was not as high as in the current study, especially in terms of number of complete doses.

Since the early stage of vaccine implementation worldwide, some articles referring to the term "post-vaccination" appeared in the literature. We observe that this has been used in a sometimes-ambiguous fashion, in that often referred to data collected in early 2021, i.e. a period where vaccination campaigns were at their earlier stage. Examples of this kind are the works by Mahmud et al. (2024; data from April 2021) in Bangladesh and Pollock et al. (2024; early 2021) in Canada. They were both referred to the first months of 2021, i.e. a period where the vaccine penetration was really small (less than 10 %) in the analysed contexts. In any case, they are important evidence of how the preferences may have changed after the introduction of the vaccines. Mahmud et al. (2024) found that women were more likely to commute by car and those over 50 were more reluctant to PT usage. Pollock et al. (2024) introduced a dummy for the vaccination status in their above-described model, finding a significant preference of vaccinated people towards the use of trains and buses and that also a partial vaccination status was more important than mandatory masks on board.

Zheng et al. (2023) considered the difference between pre-pandemic and fall 2021, finding that people in Massachusetts were more likely to commute by car and work from home. A residual fear of infection has been found also by Aaditya and Rahul (2023) in their analysis of commute trip frequency in October 2021, a date when vaccines had good penetration in the Indian population.

Studies considering contexts where vaccines were highly penetrated (e.g. data of advanced 2022) can be found in Singh et al. (2023b) for air travel preferences, Yap et al. (2023) in another VoC assessment in UK and Xu et al. (2024) in a survey on route choice for rail transit in China. In particular, Singh et al. (2023b) found a significant concern by air passengers for vaccine certification, as stated earlier. Yap et al. (2023) updated previous studies on VoC in London underground, concluding that people value crowding more negatively since COVID-19, even in a post-pandemic scenario. Xu et al. (2024) analysed the data referring to three different pandemic periods (stable, sporadic and small-scale epidemic), finding that, although the data were collected in 2022, users showed a difference in perception for different pandemic alert scenarios. None of the studies in the literature has addressed the topic of possible policy measures in PT in different pandemic contexts in a period where vaccines had been already implemented at a high penetration rate. In this sense, our study aims to conclude that there is a residual concern for a possible new wave of the pandemic, notwithstanding the high vaccine penetration and the proof of effectiveness in contrasting the most severe COVID-19 symptoms.

7. Policy implications

This section discusses relevant policy implications that can be deducted from the HCM results. In particular, Section 7.1 analyses the WTPs and attitudes in the sample, Section 7.2 discusses eventual pricing and safety measures strategies that PT providers could implement in new pandemic scenarios, based on the HCM results; Section 7.3 illustrates a simulation exercise, where the sensitivity of some important PT users segments when varying the configuration of safety measures on board has been assessed; Section 7.4 provides further lines of discussions on relevant topic concerning PT and pandemic issues.

7.1. Analysis of WTP and attitudes

Fig. 6 reports the distribution of WTP values for all those onboard characteristics that vary across the respondents in the sample, while Fig. 7 illustrates the variation in WTPs when varying the values of the latent factors.

The box plots indicate that the variation of WTPs for the allowed occupancy rate and green pass at the entrance vary to a limited extent in the sample. The variation reflects the dispersion of the latent factors in the population, which is shown in detail in Fig. 7.

The WTP for a 1 % less of allowed occupancy rate is higher for people who have a greater concern for the pandemic, with average values that are consistent in sign and value with the results reported in Table 5. This implies that people who are more sensitive to the pandemic are also more willing to pay to have less capacity allowed onboard. In the extreme case, people who are significantly feared of the virus transmission are willing to pay a positive quantity to have less occupancy rate on board even in the low pandemic scenario (green data points). The same applies to people who are less trustworthy in national government initiatives, in that $\lambda_{DNG,GP} < 0$ indicates that when the distrust in the national government initiatives (e.g. the green pass certification) increases, the WTP for having the green pass check at the entrance decreases, while a decreasing distrust reflects in a higher WTP for having this kind of preventive check on board, which is consistent with expectations. The results in terms of trust in city services are not so evident, in that the relative coefficient $\lambda_{TCS,OR}$ and the standardised values of TCS_n are lower, indicating that the WTP for the occupancy rate is less sensitive to the latter. In other words, the WTP for the occupancy rate has not a trend dictated mainly by the trust in city services (although the latter is significant in the model in Table 5), but rather on the pandemic concern.

Based on the results shown in Fig. 7, the possibility of implementing eventual soft measures and marketing campaigns can be discussed. Since the measurement data ($I_{q,n}$) are standardized with reference to their sample means and standard deviations, the rationale is that shifting the average values of the attitudes implies a vertical shift of the plots in Fig. 7. For instance, if the average sensitivity to the pandemic rises, the values in Fig. 7.*a* are shifted above, implying that people are more willing to pay for having a 1 % lower occupancy rate. In general, while the sentiment about the pandemic may be expected to shift towards a situation of relatively lesser concern, mainly due to the increasing vaccine penetration (which is incorporated in the model), the perception of citizens for city services and national government may evolve less predictably.

Information campaigns on the safety and cleanliness of PT are expected to act on the first two attitudes, in that they should make PT users safer and improve satisfaction with the services implemented in the city, as the previous literature suggests (Aghabayk et al., 2021; Shen et al., 2020). The role of marketing campaigns about the safety on board PT vehicles has been emphasized also by Kopsidas et al. (2021) analysing the case of Athens (Greece), Aaditya and Rahul (2023) in the Indian case and Iglesias and Raveau (2024) in the Chilean context. According to the proposed model, this would impact directly and significantly the WTPs for some onboard characteristics. Also, the bi-directional causal relationship between choice behaviour and attitudes should be recognized. Indeed, as testified by Kroesen et al. (2017), Kroesen and Chorus (2018) and Kroesen and Chorus (2020), pushing a change in mode choice behaviour towards more sustainable travel modes, through the implementation of tolls or new regulations for road traffic, would imply a change in attitudes, which is expected to play a major role in long-term choice behaviour in favour of more sustainable travel modes.

7.2. Pandemic evolution – optimal pricing schemes

The results of the estimated HCM can be used to obtain policy implications in terms of optimal safety measures that can be implemented in the event of a new pandemic scenario. Indeed, since the ticket price has a negative impact on the utilities of the two unlabelled options, if varying the characteristics on board with reference to a base scenario, it is possible to compensate attributes that have a positive/negative impact by decreasing/increasing the price, respectively. For instance, the results of the HCM state that, if

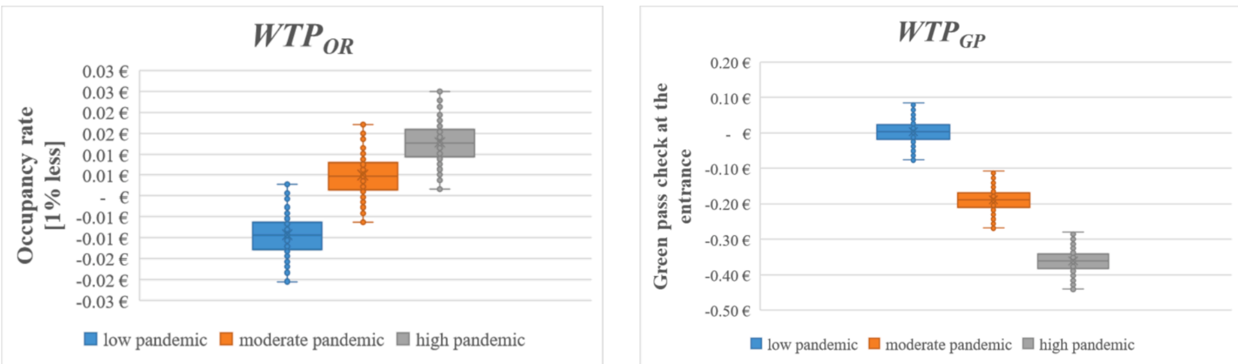


Fig. 6. Variability of WTPs within the sample.

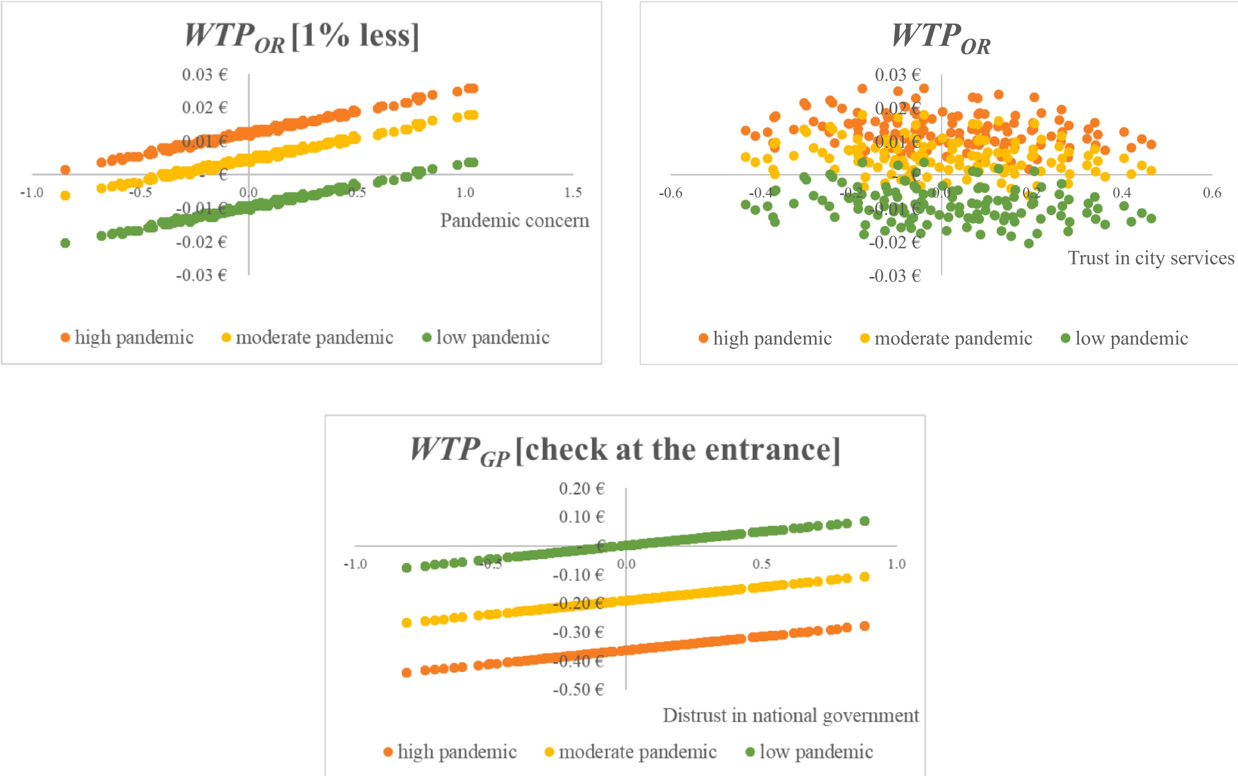


Fig. 7. Variation of WTPs with attitudes.

considering a high pandemic situation, with a base scenario of 50 % occupancy rate, PT users would compensate their negative utility for having more occupancy rate on board, with a reduced price of the PT, all the other safety measures being equal. This consideration can be important in that, as stated also in Section 6.2, a reduction in capacity can be just an apparent cost-free measure from the company side, because it can reflect in a situation where the demand for PT is not met, thus requiring additional frequency of the service. This would require mode expenditures from the company side and the potential need for further subsidies to the PT providers.

Generalizing the concept, we define two vectors $\boldsymbol{X}_p^{BASE} = \left(PR_p^{BASE}, DF_p^{BASE}, GA_p^{BASE}, AF_p^{BASE}, GP_p^{BASE}\right)$ and $\boldsymbol{X}_p^{FUT} = \left(PR_p^{FUT}, DF_p^{FUT}, GA_p^{FUT}, AF_p^{FUT}, GP_p^{FUT}\right)$ for each pandemic context $p=\{L,M,H\}$. The estimated HCM provides the utility of a certain policy configuration as a function of the variables contained in $\boldsymbol{X}_p^{BASE}$ or $\boldsymbol{X}_p^{FUT}$, the attitudes of users, in turn, function of socio-demographic and travel habits characteristics, and the coefficients of the models β, **WTP**, λ, γ and η. Notice that the estimated HCM introduces several categories c of PT users, in terms of socio-demographic characteristics and travel habits, which in turn allow for the definition of different vectors $\mathbf{WTP}_c$ and γ_c in the model. Therefore, a utility function for a certain configuration of price and safety measures can be defined for each category of users introduced in the model as $U\left(\boldsymbol{X}_p^{BASE}|\boldsymbol{\beta}, \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{BASE}\right)$ and $U\left(\boldsymbol{X}_p^{FUT}|\boldsymbol{\beta}, \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{FUT}\right)$ in base and future pandemic scenarios, respectively.

If varying one or more variables in the vector, the optimal values of the other attributes can be searched for, in order to give the same measure of attractiveness to PT users. For instance, when considering a hypothetical high pandemic alert scenario (H), with a base occupancy rate of $OR_H^{BASE} = 50$ % (consistent with the average measures set during the main pandemic waves in 2020–21), it is possible to find the configuration of ticket price and safety measures providing the same utility value with a value of occupancy rate that is higher (say 100 %). From an analytical standpoint, this means that we are searching for the vector of safety measures that leave the average utility of the users in an indifference zone.

It is possible to search for the optimal sub-vector $\boldsymbol{X}_p^{FUT*}$ as:

$$\boldsymbol{X}_p^{FUT*} = \operatorname{argmin}\left[\overline{U}\left(\boldsymbol{X}_p^{FUT}|\boldsymbol{\beta}, \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{FUT}\right) - \overline{U}\left(\boldsymbol{X}_p^{BASE}|\boldsymbol{\beta}, \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{BASE}\right)\right]^2 \tag{7}$$

where

- $\overline{U}\left(\boldsymbol{X}_p^{FUT}\right) = \sum_{c=1}^{C} p(c) \cdot U\left(\boldsymbol{X}_p^{FUT} | \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{FUT}\right)$ is the weighted average utility of the population, in the pandemic alert scenario p in future scenarios, characterized by a fixed level of allowed occupancy rate OR_H^{FUT};
- $\overline{U}\left(\boldsymbol{X}_p^{BASE}\right) = \sum_{c=1}^{C} p(c) \cdot U\left(\boldsymbol{X}_p^{BASE} | \boldsymbol{WTP}_c, \lambda, \gamma_c, OR_p^{BASE}\right)$ is the weighted average utility of the population, in the pandemic alert scenario p in future scenarios, characterized by a fixed level of allowed occupancy rate OR_H^{BASE};
- $p(c) = \prod_s p(s)$ is the share of the population belonging to the category $c = 1,\ldots C$, in turn given by an intersection of simple segments s, detected according to certain characteristics.

All the segments s introduced in the estimated HCM – i.e. within the structural equation model in Table 7 – have been considered, namely: gender (2 segments: female, male), age (4 segments: under 25, 26–35, 35–50 and over 50), education (2 segments: high or not), vaccination status (2 segments: complete/booster or not), type of vehicle most frequently used (bus/train), subscription to the PT (yes/no) and regular PT use (yes/no). Thus, the HCM considers a total amount of $C = 4^*2^6 = 256$ categories in the population. It is possible to use census data (e.g. gender, age range, education, vaccination) or, when the latter are not available, sample data (type of vehicle, PT subscription and regular use of the PT), to retrieve the share of each segment and compute the shares $p(c)$.

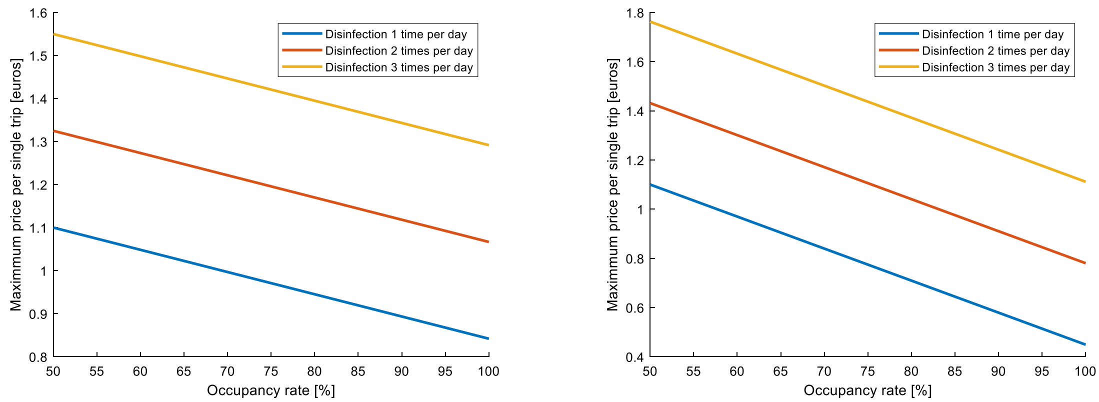
In theory, eq. (7) is a mixed integer programming problem, because the price is a continuous variable, while the others are discrete variables (*DF* is an integer, while *GA*, *AF* and *GP* are binary 1/0 variables). To make the problem a continuous programming problem, the solution can be found by setting the discrete variables to values that reflect good practices in terms of *GA*, *AF* and *GP*, thus searching just for the optimal price. In principle, choice probabilities could have been used instead of average utilities. However, as the choice probability is an increasing monotonic function of the utilities, the presented problem is equivalent. Furthermore, since the HCM is based on the data from an unlabelled choice experiment, there are no well-defined alternatives that make it interesting to work in terms of market shares/aggregated choice probabilities.

It is useful to show preliminarily the results of the solution of the problem (7) for the case where $\boldsymbol{X}_p^{BASE} = \boldsymbol{X}_p^{FUT}$ and only the value of OR_p varies. The results of the simulation are reported in Fig. 8 for moderate (*M*) and high (*H*) pandemic scenarios, for different values of the disinfection frequency.

Preliminarily notice that, in Fig. 8, the maximum allowed price, i.e. the price that gives the minimum of the problem (7), is a linear function or OR_p, consistent with the utility formulation in eqs. (6). Second, the plots in Fig. 8a and 8b have a different vertical shift when varying the disinfection frequency. This is because the WTP for increasing the disinfection frequency is higher in *H* than *M*. Third, both figures, starting from the base value $OR_p = 50$ % and corresponding base price (1.10 €), exhibit a decreasing trend of the optimal price, in that users in the sample are willing to pay to have a lower occupancy rate in *M* and *H*, as discussed in Section 6.2. However, the slope in *H* is greater than that in *M*, because, according to the HCM results, people are less compensatory in high pandemic contexts, thus the maximum price they are willing to pay, all the other measures being equal, decreases very quickly. Indeed, if leaving all the measures at their base values, people are willing to pay around 0.85 € and 0.45 € for the PT in *M* and *H*, respectively. This can be compensated by increasing the disinfection frequency on board to 2 times/day and 3 times/day in the two cases, respectively, to ensure users accept a 100 % occupancy rate on board. Assessing the safety measures that allow the price to remain equal is also important from an equity perspective, as increasing the price may lead to the preclusion of PT usage for low-income people.

Fig. 9 represents the event where other safety measures are implemented, i.e. the case where $\boldsymbol{X}_p^{BASE} \neq \boldsymbol{X}_p^{FUT}$.

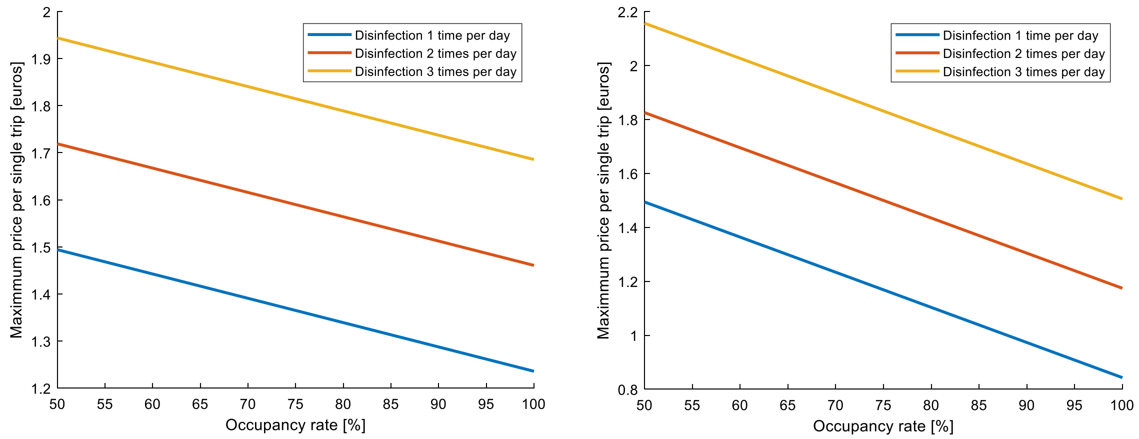
Preliminarily notice that, in this case, the plots do not start from the base ticket price (1.10 €), because in the future scenario safety measures with positive utilities, namely the ones for which users are willing to pay, are introduced. Therefore, the plots are vertically shifted in this case with respect to the equivalent plots in Fig. 8. However, all the considerations made on the trend in Fig. 8 remain valid. In this case, considering the pandemic scenario *M*, if implementing all the safety measures, namely the possibility of having air



BASE scenario: $OR_M^{BASE} = 50\%$, $GA_M^{BASE}=1$, $AF_M^{BASE}=0$, $GP_M^{BASE}=1$, $PR_M^{BASE} = 1.10$ €.

BASE scenario: $OR_H^{BASE} = 50\%$, $GA_H^{BASE}=1$, $AF_H^{BASE}=0$, $GP_H^{BASE}=1$, $PR_H^{BASE} = 1.10$ €.

Fig. 8. Optimal price when varying the occupancy rate on board in the base scenario.



BASE scenario: $OR_M^{BASE} = 50\%$, $GA_M^{BASE}=1$, $AF_M^{BASE}=0$, $GP_M^{BASE}=1$, $PR_M^{BASE} = 1.10$ €.

FUTURE scenario: $GA_M^{FUT}=AF_M^{FUT}=GP_M^{FUT}=1$.

BASE scenario: $OR_H^{BASE} = 50\%$, $GA_H^{BASE}=1$, $AF_H^{BASE}=0$, $GP_H^{BASE}=1$, $PR_H^{BASE} = 1.10$ €.

FUTURE scenario: $GA_H^{FUT}=AF_H^{FUT}=GP_H^{FUT}=1$.

Fig. 9. Optimal price when varying the configuration on board in the event of future pandemic alert scenarios ($\boldsymbol{X}_p^{BASE} \neq \boldsymbol{X}_p^{FUT}$).

exchange/filtering systems, gel on board and green pass check at the entrance, with a base disinfection frequency, users would be willing to spend more to travel by PT. In the pandemic scenario *H*, instead, PT users are less easily compensatory, in that accepting a 100 % occupancy rate would require the implementation of all safety measures, i.e. air exchange/filtering systems, gel on board and green pass check at the entrance, with a minimum of 2 times per day/disinfection at the same ticket price to leave the utility in an indifference zone. However, in this case, the required disinfection frequency is lower than the case of Fig. 8, because in Fig. 9 air exchange/filtering systems are assumed to be implemented.

7.3. Sensitivity analysis – Acceptability of safety measures

This section provides a simulation exercise to assess the acceptability of safety measures on board for relevant population segments, based on the HCM results shown in Section 6.2. We assume a base scenario with two safety measure options *A* and *B* and the possibility of opting out, consistent with the data analysed. The simulation study aims to assess the ratio of the probabilities between the two options *A* and *B* when varying one at a time of the onboard vehicle characteristics. The base values for the safety measures are: $PR_A = PR_B = 1.10$ €, $OR_A = OR_B = 50$ % of allowed occupancy rate, $DF_A = DF_B = 1$ disinfection per day, $GA_A = GA_B = 0$ (non-availability), $AF_A = AF_B = 0$ (non-availability), $GP_A = GP_B = 0$ (check onboard at random). Thus, several simulation exercises have been performed by varying one at a time of the variables over the range of the SP design, using 1000 random draws for the latent factors. The results have been reported in Figs. 10-11 in terms of $p[A]/p[B]$. The base segment of users has the following characteristics: 36–50 years age range (consistent with the average age of the population under analysis), males, average income, employed and regular travellers. Results can be extended to other segments of users. The current analysis shows the trend of the probability for the introduced categories of vaccination and ticket subscription.

Concerning the allowed occupancy rate on board, results indicate that the acceptability is lower for vaccinated people and PT subscribers. This is evidently due to the fact that users who were vaccinated at the time of the survey were more careful about the pandemic information and the contagious spread and more sensitive to the pandemic situation in general. Indeed, as discussed also in Section 6.2, the survey was disseminated during a high vaccine penetration rate period, thus the interpretation of the results is that

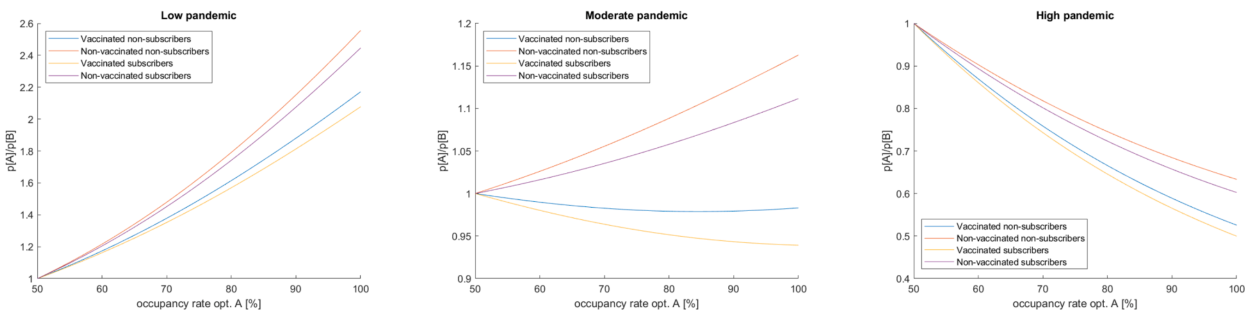


Fig. 10. Sensitivity analysis results for a variation in occupancy rate: trend of the probability ratio between two safety measure scenarios.

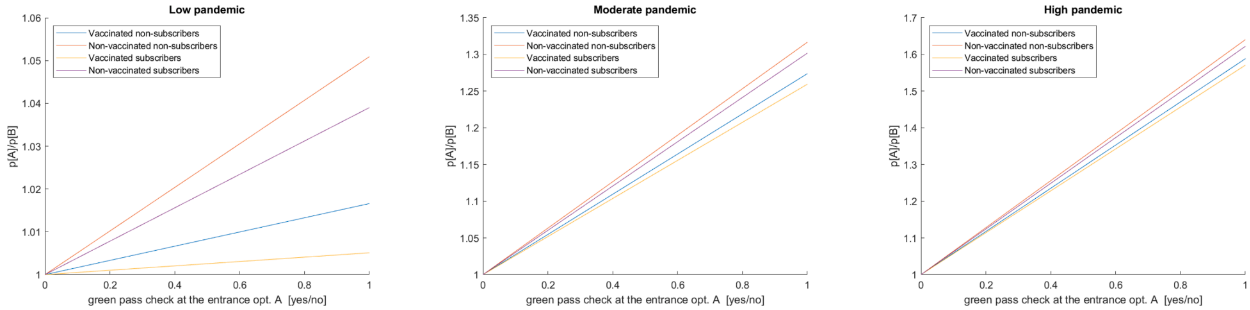


Fig. 11. Sensitivity analysis results for a variation in green pass check type: trend of the probability ratio between two safety measure scenarios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

people who were not vaccinated at the time of the survey were less sensitive to the problem and thus are more prone to accept high/low occupancy rate in low/high pandemic alert situations. Indeed, for instance, non-vaccinated/non-subscribers are 2.6 times more likely to opt for a fully allowed occupancy rate in a low pandemic scenario, while non-vaccinated /subscribers are 2.1 times more likely to opt for the same solution. In the high pandemic scenario, the findings are nearly symmetric, but with a higher share of users that would opt for a half-allowed occupancy rate. Interestingly, in the moderate pandemic case, results depend on the segment of users simulated. Indeed, the vaccinated/subscribers are about 5 % less likely to opt for a fully-allowed occupancy rate, while non-vaccinated/non-subscribers are almost 20 % more likely to opt for the same option.

Results for green pass check type analysis indicate that people are non-significantly sensitive to the presence of a green pass at the entrance in a low pandemic situation, consistent with the estimation results described in Section 6.2, while they are, on average, about 1.25 and 1.6 times more likely to opt for a solution with this type of check in the moderate and high pandemic alert situations, respectively.

7.4. Further lines of discussions

There are several dimensions to further articulate the discussion on the PT perception of safety measures, considering the recent literature on COVID-19 and post-pandemic.

Work-from-home) The impact of WFH on travel preferences during pandemic periods has been a matter of debate in the literature. Recently, Hensher and Beck (2023) investigated the role of the frequency of WFH on individual productivity and the substitution in activity patterns (mainly work and leisure) due to reduced commuting time and perceived anxiety. Liang et al. (2023) investigated the WFH frequency in three metropolises in Japan, finding that changes in lifestyle due to the widespread diffusion of telecommuting might be permanent. Müller and Wittmer (2023) studied, in particular, the preferences for virtual communications and physical business travel. Hernandez-Tamurejo et al. (2024) investigated the preferences for teleworking in Madrid, while Wang et al., (2024) estimated teleworking frequency expectations as a function of latent teleworkers segments, through a latent class approach.

This paper has directly investigated the effects of the frequency of use of PT on safety measure preferences, skipping the conceptual step for which, in principle, such a frequency endogenously reflects also WFH practices from workers. Our sample analysis confirms that the frequency of use of PT is smaller than before the pandemic, in that 75.4 % declared to use PT at least twice a week before the pandemic, while 68.4 % indicated the same after the main wave of the pandemic, which was more than a year before our survey. The difference is emphasized if considering PT users travelling at least 3 days a week (61.6 % vs 52.5 %, respectively). This is consistent with the data by Moovit (2022) for Naples and de Palma et al. (2022), who analysed various contexts worldwide, including the Italian case of Rome. Also, we deem it as consistent with the general trend to preserve social distancing observed in the responses to the attitudinal statements, where more than 76.2 % indicated a score of 4 (quite agree; 25.3 %) and 5 (totally agree; 50.9 %) to the statement "I strictly observe safety measures related to COVID −19 emergency (e.g., mask use, hand sanitization, social distancing).". The results appear significant, given the fact that refer to a period where the most important pandemic waves were over by more than one year.

Crowding) As anticipated in Section 1, one of the main bad feelings exploited during the pandemic has been the concern for shared spaces and crowded situations, such as in regular PT conditions before the pandemic. It is not surprising that, since the outbreak of the pandemic, there has been a growing interest in the assessment of the value of crowding (*VoC*; see Li and Hensher, 2011), where the latter is generally measured in terms of the value of travel time savings (*VTTs*) multiplier for different crowding conditions on board. The literature on the topic of VoC related to COVID-19 is still productive, with many published during the last two years (see Drabicki et al., 2023; Yap et al., 2023; Cho et al., 2024, Filgueiras et al., 2024, Iglesias and Raveau, 2024; Karatsoli et al., 2024; Pollock et al., 2024).

At first glance, the approach adopted in the current paper resembles the one generally adopted in the DCEs for the estimation of the VoC, but there is a significant difference in the interpretation of the choice experiment setting. A typical VoC evaluation experiment is apt to simulate a real-time decision from the perspective of a PT user that has information about the onboard vehicle crowding condition and must make a choice on whether to board the vehicle or not (e.g to wait for a second vehicle that is probably less crowded). From another perspective, the topic is related to the more general one pertaining the real-time information at bus stops

(Caulfield and O'Mahony, 2009). In the current work, we rather aim to assess the preventive choice by PT users to use or not the PT vehicle (bus/rail) and their willingness to pay more/less for each safety characteristic on board, as real-time information on crowding is not currently available for PT service in the analysed city. In other words, the current work aims at investigating different policy scenarios of the supply system (off-line), rather than the perception of users when varying the demand conditions on board (real-time). However, it should be recognized that the allowed occupancy rate of buses/trains has consequences on the crowding, in that the limitation of the capacity onboard reflects in the maximum crowding level allowed. Future steps may concern the investigation of these aspects from a demand-perspective, to evaluate how much, in different pandemic alert situations and different occupancy rate allowed, in the presence of information systems for the crowding onboard, users choose to wait or board as a function of the onboard conditions.

Time of day) Previous literature has investigated the impact of the time of day on the micro-economic behaviour of PT passengers, with main reference to the VTTs variation over the day (see e.g., Tseng and Verhoef, 2008). Arguably, time of day might have an impact on preferences for PT and, thus, for safety measures onboard the vehicles. In general, the time horizon directly impacts the demand for PT and crowding onboard, so the attractiveness of the PT differs by the time of the day. However, the issue of the time of travelling should be investigated with more in-depth individual data, possibly considering the daily trip chains and activity schedules. Also, there is an endogeneity between the travel mode choice and time of day, in that users choose to travel in a certain time interval dependent on the mode choice they make, and vice versa they may choose the travel mode as a function of their scheduled activities and constrained time of day departure. Furthermore, some researchers (see Arellana et al., 2012; Thorhauge, 2015) have emphasized how departure time is a complex choice dimension, which also potentially depends in a non-negligible way upon latent traits such as attitudes, norms and perceptions. The inclusion of data about this aspect goes beyond the scope of this work and may also be considered for further research steps.

Equity issues) Issues related to equity have been widely discussed in the literature on COVID-19 (Shandmi et al., 2020), due to the principle that there are vulnerable segments of people that are more exposed to the risk due to the COVID-19 spread or are more disadvantaged by policy actions to mitigate it. As concerns mobility, social distancing and restrictive policy measures have arguably contributed to feeding a gap between different groups (Guzman et al., 2021). This issue relates to several specific segments of a population. For instance, Mackett (2021) analysed the potential policy interventions for people with mental health conditions in UK, analysing possible barriers that could be verified in the use of public spaces and suggesting that a trained staff, clearer information systems on the PT service and better behaviour of other travellers would increase its usage. Park et al., (2022) analysed the problems related to travel habits changes in travellers with disabilities, finding that the latter has a significantly reduced number of daily trips with certain modes (e.g. taxi, paratransit, walking) with reference to travellers without disabilities, but the same does not happen to PT users. A similar conclusion applies to the findings by Hossain et al. (2023), who analysed data from 2021 on other disadvantaged groups, such as those with low income or belonging to ethnic minorities, who were found to be inclined to continue using PT frequently after the pandemic. Analogously, the analysis of smart card data from Stockholm by Almlöf et al. (2021) concluded that high-income groups had a significantly higher percentage reduction in PT usage. In general, findings from the literature suggest different considerations in applying eventual policy actions to manage future emergencies. The most important equity issues relate to the ticket price and capacity on board. Indeed, as discussed by De Vos (2020), the occupancy rate on board should not be drastically reduced, while Gutiérrez et al. (2021) suggested that ticket fares should not be increased during emergencies. In this sense, the exercise proposed in Section 7.2 is important, as it allows to understand how to equip vehicles as not to provide barriers to disadvantaged groups in terms of price.

The policy measures for onboard safety characteristics should be implemented in consideration that service must not be significantly precluded to people travelling in areas of the city where PT is less accessible. Thus, future research steps could investigate how the allowed capacity on board could vary as a function of the areas covered by different PT lines. Furthermore, eventual subsidy schemes should consider also people with other disadvantages, such as users with disabilities and those belonging to minority groups.

Mode choice) The literature on the mode choice in time of COVID-19 is very wide, as testified by the review proposed in Section 2. As already mentioned, several works have investigated the mode choice preferences by introducing also the effect of safety measures, especially in PT modes (e.g. bus/metro) or intermediate forms of collective services (e.g. paratransit, on-demand services). As earlier evidence suggested, PT would have been the most hit travel mode during the pandemic. Indeed, since the first lockdowns, the literature suggested that a significant shift to car and private modes was occurring. More in general, the resort to the so-called "unsharing" (Corazza and Musso, 2021) should have been expected in a near future. The analysis by Awad-Nunez et al. (2021*a*) emphasized that the same concern showed by PT users for sanitisation, cleanliness of vehicles and the possibility that vehicles hosted infected users on board was evident in car-sharing, taxi and ride-hailing users. Users of bike and scooter sharing showed themselves also very feared of toughing parts of the shared vehicles, thus being willing to spend more for covers or helmets that did not touch the mouth, eyes and nose of other users. The current paper analyses the specific segment of PT users, as done by Bwambale et el. (2023). Although the unlabelled choice experiment used in this paper is more appropriate for capturing trade-offs, WTPs and the relative importance of attributes, as well as it is able to capture other aspects such as the interaction between WTPs and latent factors or the effect of different pandemic alert scenarios, it does not capture the substitution pattern across modes and does not consider level-of-service attributes, such as in-vehicle/out-of-vehicle travel time, travel time reliability, transfers and so on. Notably, mode choice experiments including many attributes and mode alternatives may induce fatigue, with a risk of bias in the responses, inevitably affecting the statistical quality of the results for what concerns specifically safety measures. This is the most likely reason why stated mode choice experiments in the literature have often introduced a smaller number of safety measures on board than in the current study. Investigating properly the safety measures on board with a mode choice experiment would have required respondents to trade between 5/6 alternatives and 10 or more SP attributes, thus leading to the need to scarify some safety measure variables or to detail less the level-of-service ones (e.g. not considering some of the travel time rates in the SP variables). Future works may investigate the possibility of investigating trade-offs between level-of-service attributes, price and safety measures, to investigate also the elasticity of other modes (e.g. active modes or private motorized modes) when varying the safety measures on board the PT vehicles and the information about them to users. Such a kind of evaluation should be conducted with customized discrete choice experiments, with proper strategies of bias mitigation and attribute-non-attendance processing.

8. Conclusions

This paper has investigated the willingness to pay (WTP) and attitudes of PT users in the city of Naples (Italy) for onboard vehicle characteristics, referring to three hypothetical pandemic situations, in a period where COVID-19 vaccines were highly penetrated within the Italian population. The advantage of treating the information on the actual vaccination status is that vaccine data are constantly available and updated at an aggregate level, thus making it possible to treat them as observable attributes and eventually making predictions on data (e.g. time-series analysis). A panel SP survey with attitudinal questions has been disseminated in two waves (April-May 2022 and June-July 2022), through the social media channels of the main bus operator of the city, namely Azienda Napoletana per la Mobilità (ANM). An Exploratory Factor Analysis (EFA) has been conducted to extract the main three latent factors explaining the variance of attitudinal responses, leading to the consideration of the following three latent factors in explaining stated choices: pandemic concern, trust in city services and distrust in national government initiatives. A hybrid choice model (HCM), specified in WTP space and incorporating the interaction effects between the vehicle onboard characteristics – i.e occupancy rate, disinfection frequency, gel availability, air exchange/filtering, green pass check at the entrance – and the analysed latent factors, has been finally estimated to analyse the data. Several policy implications that are useful for transport companies, in terms of ticketing strategies and policy actions to be implemented during eventual future pandemic alert situations, have been derived.

The results indicate that people have a significantly different sensitivity to almost onboard vehicle characteristics as the pandemic alert rises. In particular, the allowed occupancy rate onboard has an opposite impact on choice behaviour in low and high pandemic situations, being positively/negatively perceived in low/high pandemic situations. PT users of the sample are willing to pay almost 1.20 euro cents per 1 % more/less of the allowed occupancy rate onboard in low/high pandemic scenarios. Also, the WTP for increasing the daily disinfection frequency and having air exchange/filtering rises as the pandemic alert situation becomes more severe and for individuals who are more pandemic-concerned. The WTP for a preventive green pass check at the entrance becomes significant in situations of moderate and high pandemics and rises as the distrust in national government initiatives decreases. The trust in city services attitude has a positive and significant impact on WTP for occupancy rate. The availability of gel onboard is the less significant attribute in the analysis. In general, the relative importance of attributes testifies that users have a different ranking of importance as the pandemic situation changes. Except for the ticket price, which is the most important attribute in all the pandemic situations, the disinfection frequency is the most important one in high and moderate pandemic situations, while the allowed capacity on board is the most important one in a low pandemic situation. The allowed capacity on board, in particular, is highly important also in a high pandemic situation, although with a different sign, as discussed, while it is much less important in moderate pandemic situations.

The analysis of WTPs indicates that assuming a base scenario of 50 % occupancy rate in the high pandemic alert scenario and the current safety measures and ticket price, the potential loss of demand for PT may be compensated by implementing more onboard safety measures, e.g. the green pass check at the entrance and one between air exchange/filtering and a disinfection onboard more per day. Furthermore, we discussed how PT users can positively shift their WTPs with marketing campaigns about the quality of the safety of the vehicles and the city services in general, as well as the national government initiatives. By implementing such a kind of soft measures, one may expect a positive shift in the three analysed attitudes (less concern for the pandemic situation, more trust in city services and national government) that, according to the modelling framework used in this paper, would imply that PT users are more willing to pay for PT in the city.

Based on the estimated HCM, we also simulated the optimal price and safety measures in the event of new pandemic scenarios in different conditions of capacity allowed on board, considering the 256 categories of PT users introduced in the structural equation model of the HCM. In particular, we considered the average utility in the population for a certain configuration of safety measures in the base scenario, consistent with the ones prevailingly implemented during the past pandemic waves, assuming an occupancy rate on board of 50 % in moderate and high pandemic scenarios. Then, we searched for the optimal values of price and safety measures necessary to leave the average utility in an indifferent zone when increasing the capacity on board. We found that the negative effect of the pandemic can be compensated effectively in a moderate pandemic alert scenario, by implementing base safety measures on board, such as gel and air exchange/filtering systems. In a high pandemic scenario, a disinfection frequency of 2 times per day, the availability of the gel on board, the air exchange/filtering systems and a green pass check at the entrance would allow the ticket price to remain unchanged. Otherwise, in situations where the PT providers cannot ensure such safety measures, the ticket price per single trip should be significantly reduced, to overcome further losses of demand. This is an important point in terms of equity, as discussed in Section 7.4.

Finally, we implemented another simulation study for representative segments of users, assessing the ratio of probabilities between two safety measure scenarios differing in one at the time of the safety measure values. The latter analysis testifies that non-vaccinated/PT subscribers are more likely to accept a full occupancy rate scenario with a ratio of 2.6/1.15 in low/moderate pandemic alert situations, respectively, while the ratio is about 0.75 in a high pandemic alert situation.

The current study has some limitations that should be considered before generalizing the results. First, the study has made use of an opportunistic sampling strategy. The sample representativeness may be improved, and the sample size increased in future surveys. Second, the data are inevitably affected by the sentiment about the pandemic at the time of the survey dissemination, currently captured with cross-sectional attitudinal data. It is advisable, from the company and the city planning perspective, to repropose the attitudinal questionnaire, to incorporate a longitudinal analysis in the proposed framework, updating the data periodically. Finally, the results from this study could complement the implementation of a mode choice model, to assess the elasticity of the demand for PT in the city, when varying the pandemic situation, the safety measures on board and PT tickets.

CRediT authorship contribution statement

Fiore Tinessa: Conceptualization, Formal analysis, Methodology, Resources, Software, Writing – original draft. **Concepción Román Garcia:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Fulvio Simonelli:** Funding acquisition, Writing – review & editing. **Andrea Papola:** Supervision, Writing – review & editing. **Francesca Pagliara:** Supervision, Writing – review & editing.

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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Appendix A:. COVID-19 in Italy and the Campania region

On March 9, 2020 the Italian Government jointly issued the declaration of state of emergency and implementation of the lockdown, with the start of the campaign named "Io Resto a Casa". As a consequence of the lockdown, most activities were closed and major restrictions were applied to PT services. According to Falchetta and Noussan (2020), there was a 90 per cent reduction in PT use during the spring 2020 lockdown period in Italy. Since that first lockdown implementation, many other phases have followed in the country. The second important phase was experienced in the autumn of 2020 and saw an unpreceded upsurge of cases, which led to the introduction of the colouring system of Italian regions (yellow, orange, red) according to regional case density and hospital pressure, based on the data collected by the Italian Ministry of Health. This phase covered most of autumn 2020 and winter 2021, in almost all Italian regions. Each region, depending on its area colouring, experienced more (red) or less (yellow) stringent restrictions, in terms of business closures, the requirement not to leave home, the mandatory buffering for return to work, school closures, and mobility restrictions. The Campania Region has been the region with the highest share of time in the red colouring zone in Italy (around 20 % of the period until the end of 2021). The third major phase began partially overlapping with the second one and saw the introduction of COVID-19 vaccines and the green pass certification, namely an electronic tool introduced by the Italian Ministry of Health, aimed to detect people who could access certain facilities, including PT services. This certification, through personal tracking on the National Sanitary System data bank, allowed access to different activities depending on the number and type of vaccines received by each citizen. Figure A.1 reports on the trend of new infections and deaths in Italy, with the data being captured by OurWorldinData dataset (Our World in Data, 2023).

The first peak of the pandemic (spring 2020) shows an apparent abnormal trend, in that the ratio of deaths per infection was very high. This can be explained by the fact that, in the earlier pandemic stages, there was an underestimation of the actual infections (Figure A.1a) – due to the fact that household swabs were poorly spread in the population and infection detection was prevailingly left to hospitals – and a higher mortality rate of the first variants of the SaRS COV2. Italy was, in particular, the country with the highest mortality worldwide during the spring 2020.

At the beginning of 2021, the vaccines were introduced gradually for different age ranges in Italy, the main ones being: AstraZeneca, Pfizer/BioNTech, Moderna and Johnson&Johnson. The primary vaccine cycle consisted of two doses for the bi-dose vaccine (AstraZeneca, Pfizer/BioNTech, Moderna) and one for the mono-dose (Johnson&Johnson). A booster dose has been declared as necessary for obtaining the green pass certification for all those people who have completed the primary cycle or contracted the virus for more than 120 days.

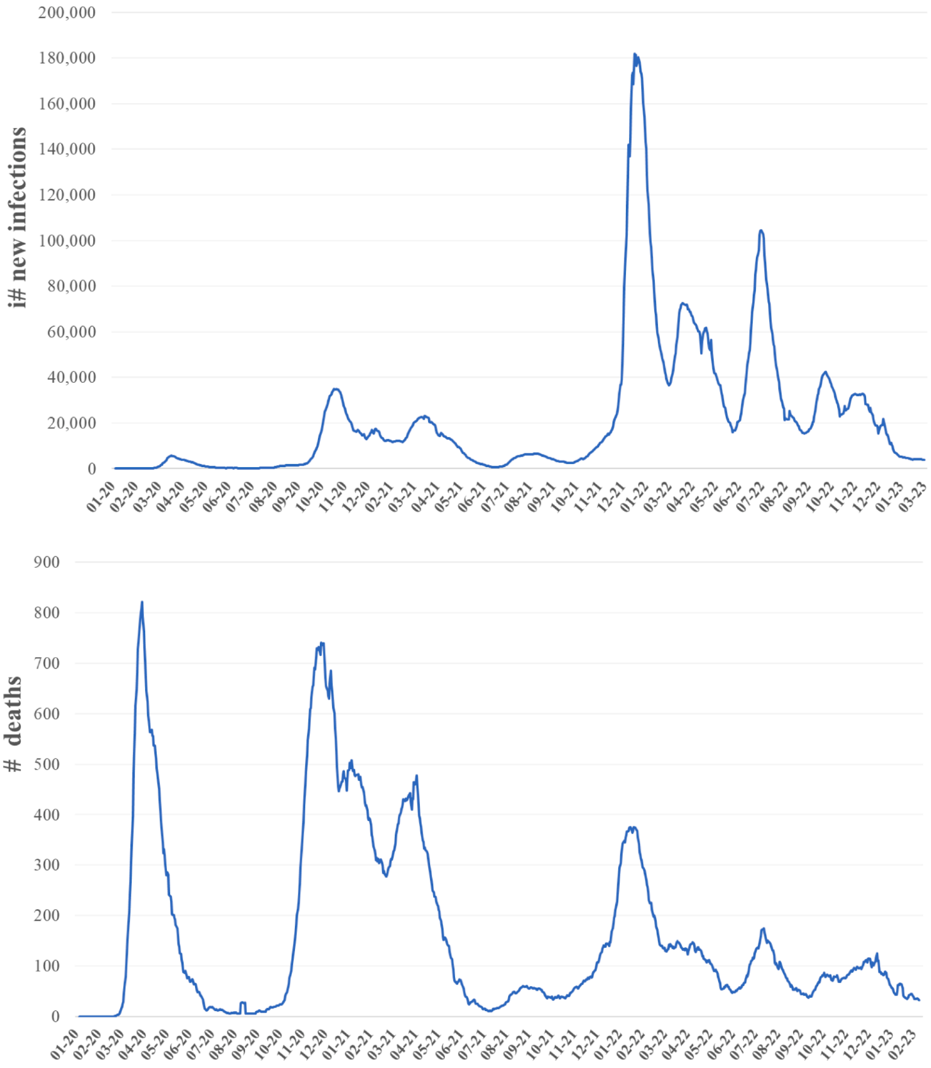

Fig. A1. Trend of infections (top) and deaths (bottom) in the Campania region.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2024.104301.

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