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A study on the factors that influenced the choice of transport mode before, during, and after the first lockdown in Milan, Italy

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ABSTRACT

COVID-19 measures implied many changes to travel behaviour and transport mode choice during the pandemic. This study seeks to understand what individual characteristics and travel attributes are related to transport mode choice before, during, and after the first lockdown in Italy. Based on an online survey (carried out in May 2020 in Milan), three multinomial regression models are presented. The results show that and in which measure parameters regarding distance and duration of daily travel are markedly related to transport mode before the lockdown. However, these factors are less significantly associated with the transport mode during and after the lockdown. Meanwhile, factors such as *Preferences* and *Worry about using public transport* have more significant relationship with the modal choice during the pandemic. Regarding individual characteristics, women are more likely to use active mode during and after the lockdown. Additionally, two personality traits of *Agreeableness*, and *Openness to experiences* are related to transport mode during and after the lockdown, respectively. Overall, this study reveals that in addition to socio-demographic factors, other variables such as worry about using public transport, preference, and personality are associated with the choice of transport mode during the lockdown.

1. Introduction

COVID-19 measures such as lockdown, social distancing, and smart working implied notable changes in travel behaviour and choice of transport mode. The overall daily mobility and public transport ridership diminished significantly. In the United States, the increase in infection rate reduced mobility by 2.31 % (Engle et al., 2020). In Japan and Hong Kong, human mobility decreased by around 50 % (Yabe et al., 2020; Zhang et al., 2021). Similarly, in Spain, Germany, and Italy mobility dropped by around 80 % during the pandemic (Bernhardt, 2020). Italy, in particular, was one of the first countries that implied strict measures to decrease mobility and stop the transmission of the virus (AbouKorin et al., 2021; Campisi et al., 2020). Until March 2020, 26 provinces severely limited the movements between cities by 50 % (Caselli et al., 2020).

Besides, shifts from shared travel mode towards using private mode and active mobility such as walking and cycling were reported that was mostly due to the negative perception of contagion and the possibility of smart working (Braut et al., 2022; Li et al., 2022; Nikiforiadis et al., 2022; Nikolaidou et al., 2023). For instance, in some cities such as Milan and Madrid, the ridership decreased by 88 % during the pandemic (Navarrete-Hernandez et al., 2023). In Stockholm and Tampere, the decrease in public transport ridership was 60 %, and 70 % respectively (Jenelius & Cebecauer, 2020; Tiikkaja & Viri, 2021). Also, in Vienna, Innsbruck, Oslo, and Agder between 67 % and 82 % loss of public transport patronage was reported (Rasca et al., 2021).

Recent studies demonstrate that certain travel attributes (e.g., travel distance and travel time), and individual characteristics (e.g., socio-demographics and perceptions) have contributed to the choice of transport mode during the pandemic (Abduljabbar et al., 2022). It is evident that several factors such as gender, income, car ownership, travel distance, and travel purpose were significant predictors of mode choice during the pandemic (Abdullah et al., 2020; Abdullah et al., 2022; Amin & Adah, 2022; Chen et al., 2022; Nikolaidou et al., 2023; Schmidt et al., 2021; Teixeira & Cunha, 2023; Zafri et al., 2022).

While efforts have been made to identify relevant factors to the choice of transport mode during the pandemic, there is little known about the significance of these parameters on the choice of transport mode before, during, and after the pandemic, especially in Italy. Particularly, there is still a lack of knowledge about the relevance of certain individual characteristics such as personality traits to the choice of transport mode during and after the pandemic, and whether these

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factors were influential on the choice of transport mode before the lockdown. It is unclear how much people's preferred mode of transportation mirrored their actual travel mode behaviour after the lockdown, according to the literature. This comparison could possibly shed light on the accuracy of post-pandemic travel behaviour predictions.

Therefore, this research tries to understand how and why travelling choices changed or people wished to change due to the lockdown and how they presume to behave after the lockdown as a result of their experience. Firstly, it is hypothesised that travel and individual characteristics are associated with the choice of transport mode before, during, and after the first lockdown. Secondly, it is also assumed that these factors would play more important roles in the choice of transport mode during and after the pandemic rather than before the pandemic. To answer the research question and the hypotheses, primarily, previous studies related to this topic are reviewed in Section 2. Then, based on an online survey carried out in May 2020 in Milan, three non-linear regression models for the choice of transport mode before, during, and after the lockdown are presented in Section 3. Subsequently, the results of the models are presented in Section 4, and the discussion of the outcomes is developed in Section 5. Finally, the conclusions of this study are drawn in Section 6.

2. Literature review

2.1. Travel mode choice before COVID-19

In the last decades, a growing body of literature has investigated the influence of various individual and travel characteristics on the choice of transport mode. Several travel attributes such as duration of travel and travel distance are associated with the choice of travel mode (Ding et al., 2017). the structure of the city, and the location of the workplace influence commuting time (Cheng et al., 2019). Longer commutes can cause traffic congestion, and using motorised vehicles. While, compact cities can foster shorter daily travel time and consequently encourage the use of active modes (Both et al., 2022). Besides, some individual (socio-demographics) characteristics such as gender, age, income, and availability or possession of transport mode significantly determine travel mode behaviour. For instance, findings indicate that being a woman and being at a younger age is positively associated with choosing public transport and active modes over private cars (Ashrafi & Neumann, 2017).

2.2. Travel mode choice during COVID-19

The COVID-19 measures imposed several changes to travel behaviour and choice of transport mode during the pandemic (Zhang et al., 2021). The majority of the studies have reported a general decrease in overall daily mobility (Li et al., 2022; Monterde-i-Bort et al., 2022), a reduction in public transport ridership (Abduljabbar et al., 2022; Abdullah et al., 2022; Zafri et al., 2021), and a switch (shift) from shared travel modes towards using private modes (Abdullah et al., 2020; Braut et al., 2022; Das et al., 2021; Dingil & Esztergár-Kiss, 2021; Eisenmann et al., 2021; Padmakumar & Patil, 2022) and active modes (Kyriakidis et al., 2023; Schaefer et al., 2021; Tarasi et al., 2021). In many countries like Italy, and Germany, mobility dropped by around 80 % during the pandemic (Bernhardt, 2020). Pozo et al. (2022), by using real ticket validations in Spain, reported that, at the peak pandemic, overall ridership diminished by 95 %, and it tended to rebound very slowly and it could gain half of its pre-pandemic level.

Several travel attributes are found relevant to the change in travel mode during the pandemic. Some factors such as travel distance (Abdullah et al., 2020; Dingil & Esztergár-Kiss, 2021; Harrington & Hadjiconstantinou, 2022; La Paix, 2021; Schmidt et al., 2021), travel time (Abdullah et al., 2022; Das et al., 2021; La Paix, 2021; Luan et al., 2021; Ulahannan & Birrell, 2022), travel purpose (Abdullah et al., 2020; Abdullah et al., 2022; Bhaduri et al., 2020; Chen et al., 2021; Echaniz et al., 2021; Khaddar & Fatmi, 2021; Shakibaei et al., 2021), travel cost (Abdullah et al., 2022; La Paix, 2021; Luan et al., 2021), travel frequency (Abdullah et al., 2020; Abdullah et al., 2021), car or motorbike ownership (Abdullah et al., 2020; Abdullah et al., 2021; Chen et al., 2021; Schmidt et al., 2021; Zafri et al., 2021), overcrowding (Das et al., 2021), and comfort (Abdullah et al., 2022) are found relevant to the transport mode during the pandemic.

Abdullah et al. (2020), based on an online survey with (N = 1203 respondents) from various countries and using multinomial logistic regression reported that shorter travel distance was positively associated with using private and active modes versus public transport. They also reported that the distance of travel during pandemics has become shorter and daily travels are less frequent due to pandemic measures. Besides, Schmidt et al. (2021), by using data from a German population (N = 3092) show that the travel distance was significantly associated with higher frequencies of bike use during the lockdown compared to the same period in 2019. Chen et al. (2022), using data (N = 394) collected from the Netherlands, reported that time-related travel attributes are related to the selection of transport modes. They found that travel time negatively impacts all transport modes and individuals tend to select a transport mode that can provide minimal travel duration.

Chen et al. (2021), based on an online survey (N = 513) collected from China using a multivariate logistic regression model, showed that respondents with certain limitations such as limited access to public transportation infrastructure and low access to a private car are obliged to rely on non-motorised modes and active modes. Similarly, Dingil and Esztergár-Kiss (2021), by using data from an international survey (N = 585), demonstrated that people with longer travel distances are less likely to change their transport mode.

In addition, some socio-demographic characteristics such as gender (Abdullah et al., 2020; Abdullah et al., 2021; Abdullah et al., 2022; Cusack, 2021; Das et al., 2021; Khaddar & Fatmi, 2021; La Paix, 2021; Schaefer et al., 2021; Tarasi et al., 2021), age (Bhaduri et al., 2020; Chen et al., 2022; Das et al., 2021; Gramsch et al., 2022; Zafri et al., 2022), income (Abdullah et al., 2021; Abdullah et al., 2022; Bhaduri et al., 2020; Das et al., 2021; Dingil & Esztergár-Kiss, 2021; Gramsch et al., 2022; Javid et al., 2021; La Paix, 2021; Pozo et al., 2022; Schaefer et al., 2021; Shakibaei et al., 2021; Zafri et al., 2021; Zafri et al., 2022), education (Abdullah et al., 2021; Chen et al., 2022), marital status (Chen et al., 2022) were relevant to travel mode during the pandemic.

Das et al. (2021), based on an online survey (N = 840) in India, used a logistic regression model and reported that male young respondents are more likely to use public transport. Also, high-income and elderly people who had access to a private car had a higher probability to use a car. Campisi et al. (2020), based on an online survey (N = 431) and applying an ordinal regression model, found that women were less probable than men to walk during the pandemic in Sicily, Italy. Scorrano and Danielis (2021) found that women were more disposed to walk and cycle than men, and younger people (36–65 years old) compared with older adults (over 65 years old group) were more inclined to walk during the pandemic in Trieste, Italy.

Schaefer et al. (2021), by analysing a survey with over 4.000 respondents in the Hanover Region and using multivariate regression models showed that people who had higher income tended to use a car more often for their daily travel during the pandemic compared with before the pandemic. According to their results, age had a significant negative influence on using a car which means that older participants were less likely to use a car during the pandemic. However, they found out that age had a minor effect on cycling during the pandemic. Cusack (2021) utilised data from an online survey (N = 213) in the USA, and compared respondents who commuted using active modes to those who did not use them. The findings based on a logistic regression model showed that gender and race were significantly associated with active modes; indicating that females and non-white respondents were less likely to commute using active modes of transport.

In addition, it is widely discussed that travel mode changes are due to people's perception of fear of COVID-19 (Abdullah et al., 2020; Abdullah et al., 2021; Abdullah et al., 2022; Chen et al., 2021; Chen et al., 2022; Cusack, 2021; Das et al., 2021; Dingil & Esztergár-Kiss, 2021; Echaniz et al., 2021; Nikiforiadis et al., 2020; Schaefer et al., 2021; Shakibaei et al., 2021; Shibayama et al., 2021; Zafri et al., 2022). For instance, Shibayama et al. (2021), based on an international online survey using >11,000 responses found that 72 % of respondents expressed that the motivation to change from public transport to other modes is the higher infection risk of public transport. Echaniz et al. (2021), by an online survey (N = 336) in Spain, found that individuals' perception of the safety of the modes of transport against the virus influenced their choice of transport mode during the pandemic. They also compared the cleanliness perception before and during the pandemic and they found that the percentage increased from 50 % to 90 % before and during the pandemic, respectively. Gnerre et al. (2022) based on an online survey conducted in Italy with 517 responses, reported that risk perception has diminished the probability of the overall level of travel satisfaction.

Furthermore, few researchers have observed the relationship between personality traits and preferred transport mode during the pandemic. Roos et al. (2022) based on a Web-based panel (N = 1068) in Sweden, have examined the influences of personality traits on the choice of transport mode. They found that car driving is influenced by a high degree of Conscientiousness, and a low degree of Openness. Use of public transport is affected by a low degree of Conscientiousness, a high degree of Openness, and a high degree of Agreeableness. Also, Malichova and Tokarcikova (2021), by collecting data from students in Croatia, Slovakia and Romania identified individuals' factors influencing interest in bike sharing. Their findings based on a multinomial logistic regression confirmed the influence of neuroticism and openness on interest in bike-sharing on specific interest categories. Moderate Neuroticism was negatively related to bike-sharing, while low Openness was positively related to bike-sharing.

2.3. Travel mode choice after COVID-19

Many recent studies have also studied the transport mode behaviour after lockdown. Findings indicate that there would be a high tendency towards using unshared modes of transport such as private car and active mode after the pandemic (Awad-Núñez et al., 2021; Chen et al., 2022; Das et al., 2021; Echaniz et al., 2021; Harrington & Hadjiconstantinou, 2022; Luan et al., 2021; Monterde-i-Bort et al., 2022; Nikiforiadis et al., 2020; Nikiforiadis et al., 2022; Rodríguez González et al., 2021; Schmidt et al., 2021; Shibayama et al., 2021; Tarasi et al., 2021; Thomas et al., 2021). Monterde-i-Bort et al. (2022) based on a survey (N = 636) from ten countries, reported that the use of private car and walking rebounded and it almost went back to normal (before the pandemic). In particular, the use of public transport increased, though it did not reach the level before the pandemic. Their findings indicate that the only mode of transport that was not influenced by the pandemic was cycling.

Nikiforiadis et al. (2020) based on a survey in Greece and with 223 responses, showed that bike-sharing is more likely to become a more desirable mobility option for people who were formerly private cars commuters (as passengers) and people who were bike-sharing users before the pandemic. Similarly, Harrington and Hadjiconstantinou (2022) based on an online survey (N = 725) in the UK, studied the transport mode that respondents may use in post-pandemic. They reported that when restrictions are lifted, 20.5 % of public transport and 10.1 % of car pre-pandemic commuters might switch to active mode.

Echaniz et al. (2021) by modelling respondent preferences for transport mode after the lockdown showed that the use of public transport significantly increased compared with the transport mode during the pandemic, though public transport had the lowest value compared with other modes. Schmidt et al. (2021) regarding the consequences of the pandemic measures on the choices of daily travel mode and on respondents' wishes for future mobility, found that participants had a higher desire for active mobility more frequently (44.3 %). Similarly, Awad-Núñez et al. (2021) based on a survey conducted in Spain (N = 984) and using the binary logit model, reported that >75 % of respondents would accept car use restrictions after the return to normal and they would change the primary transport mode towards a sustainable mode of transport.

Despite emerging literature on the influence of the pandemic on travel mode behaviour (Abduljabbar et al., 2022), still there are some gaps in understanding. Most of the findings refer to the fear and perceived risk of using transport modes and little is known about the relevance of travel and individual factors to travel mode behaviour, especially in Italy. Also, very few works have analysed the association between individual factors especially personality traits with travel mode during and after lockdown. To fill these gaps, the current study, based on empirical evidence, (i) provides useful information about the daily travel behaviour of individuals during the first lockdown in Italy. (ii) it reveals the relation between the choice of transport mode during the lockdown and individual and travel characteristics. (iii) also, the association between personality traits and preferences with modal choice during and after the pandemic are presented.

3. Data and modelling

3.1. The survey

In this study, an online survey was conducted in May 2020 in Milan, and 1025 responses were collected. The online questionnaire was available for official channels of the polytechnic university of Milan (Politecnico di Milano), the Engineer Association of Milan, the Municipality and Lombardy Region, and students living in Milan. For ethical concerns, only a summary of statistical results is presented in Table 1. The strength of this survey, which is not a mere convenience sample, is that it includes different categories of people regarding demographic factors (such as age, gender, and income) and diversity in using various transport modes. The participants were mostly employees, and they experienced a change in their daily travel behaviour owing to pandemic measures such as stay-at-home and smart working. We compared survey data on gender, age, and income with data available on the population of Milan's metropolitan region. While the gender and age distributions appear to be quite similar, the income distributions are noticeably different for low- and high-income groups. The general numbers include all individuals, such as inactive individuals or individuals with high incomes, who are unlikely to be reflected in this type of recruiting poll. This can help explaining the discrepancies.

The survey was designed to get information about:

- socio-demographic and individual characteristics,
- daily travel characteristics (such as transport mode before, during, and after lockdown),
- and personality traits.

3.2. The models

A multinomial logistic regression model is suitable to describe and test hypotheses about relationships between a categorical, nominal, or ordinal dependent variable and one or more categorical or continuous explanatory variables. This model provides a way to obtain the estimated probability of belonging to a specific category of data and the estimate of the odds ratio of independent variables with high efficiency and reliability (Peng et al., 2002; Scott et al., 1999). Moreover, we can obtain the estimates of the net effects of a set of explanatory variables on the dependent variable (Morgan & Teachman, 1988).

The general model for probabilities p_i for a multinomial regression (MNR) with three alternatives in output (i = 1, 2, 3) and five independent variables, is the following:

Table 1
Overview of the variables used in the study.

	Variables	No. of classes	Percentages						
Individual characteristics	Residency in the metropolitan area of Milan (living)	2	In	Outside					
			77%	23%					
	Gender	2	Men	Women					
			60%	40%					
	Age (years old)	7	15–20	21–30	31–40	41–50	51–60	61–70	>71
			2%	13%	19%	29%	22%	11%	4%
	Monthly income (€)	4	<1000	1000–2000	2000–3000	>3000			
			5%	47%	26%	22%			
	The desire to change lifestyle	3	<3	4–5	6–7				
			22%	44%	34%				
	Health condition (self-reported)	3	1–3	4–5	6–7				
			10%	38%	52%				
	Enjoyment of smart working or studying	5	Not at all	A little	Somewhat	Very	Extremely		
			3%	17%	39%	27%	14%		
Travel characteristics	Area of movement within or outside of the metropolitan area of Milan	4	Inside	From inside to outside	From outside to inside	Only outside			
			60%	10%	26%	4%			
	Mode of transport before L-D	3	Auto	Public transport	Active mode				
			24%	47%	29%				
	Possession/availability of mode of transport	6	Nothing	Auto	Bicycle	Motorcy cle	Electric scooter	Other	
			5%	49%	34%	9%	2%	1%	
	Preference for daily travel after L-D	4	Private car	Walk or cycle	Public transport only emergency	Public transport			
			42%	28%	17%	13%			
	Duration of daily travel before L-D [min]	4	<15	15–30	30–60	>60			
			15%	25%	37%	23%			
	Purpose of daily travel before L-D	4	Work	School or university	Free time	Other activities			
			51%	4%	30%	15%			
	Satisfaction with public transport	6	Not using public transp.	Not at all	A little	Somewhat	Very	Extremely	
			7%	7%	20%	34%	23%	9%	
	Mode of transport during L-D	3	Auto	Public transport	Active mode				
			46%	8%	46%				
	Mode of transport after L-D	3	Auto	Public transport	Active mode				
			49%	16%	35%				
	Worry about using public transport	5	No worry	A little	Somewhat	A lot	Extremely		
			8%	12%	27%	29%	24%		
	Information-seeking about public transport	5	Not at all	A little	Somewhat	A lot	Extremely		
			6%	7%	18%	30%	39%		
Personality	Extraversion	3	1–3	4–5	6–7				
			24%	50%	26%				
	Agreeableness	3	1–3	4–5	6–7				
			2%	28%	70%				
	Conscientiousness	2	4–5	6–7					
			15%	85%					
	Emotional stability	3	1–3	4–5	6–7				
			5%	30%	65%				
	Openness to experiences	3	1–3	4–5	6–7				
			6%	56%	38%				

CBL, choice before lockdown, CDL, choice during the lockdown, CAL, choice after the lockdown.

$$ln\left(\frac{p_1}{p_3}\right) = \propto_1 + \beta_{11}X_1 + \beta_{12}X_2 + \beta_{13}X_3 + \beta_{14}X_4 + \beta_{15}X_5 \tag{1}$$

$$ln\left(\frac{p_2}{p_3}\right) = \propto_2 + \beta_{21}X_1 + \beta_{22}X_2 + \beta_{23}X_3 + \beta_{24}X_4 + \beta_{25}X_5 \tag{2}$$

where, for both equations, X_i are the explanatory variables that can be categorical or continuous, while the outcome is nominal or ordinal respectively. α_1, α_2, β_{ij}, are parameters, estimated by the maximum likelihood method.

Three variables, related to the choice of transport mode before, during, and after lockdown, are considered as dependent variables. The set of models developed to analyse the choice of transport mode.is then:

The users were classified into three user groups (classes) of private car, public transport, and active mode (bicycle, walking) users. It is noteworthy that the survey was carried out when people were still under the first lockdown and the choice of transport mode after lockdown represents their preferences and interests for their daily travel after the lockdown. This argument is related to the preferences and attitudes of people during the pandemic, as discussed in Section 2.

Other variables that were used as the explanatory variables are presented in Table 2 (only those resulted significantly in models). They are divided into three subsets: namely, general (G), transport (T), and personality (P). Regarding individual characteristics, firstly, information about socio-demographic characteristics including gender, age, and monthly income was obtained. Also, relating to activity, some variables such as the hours they devoted to studying or working, doing smart-working/studying, and the enjoyment of smart activity were also included. Besides, questions related to the health condition (self-reported) and physical activity before and during lockdown were asked. Some information related to the residency inside/outside the metropolitan area of Milan, the hours spent out of the home before lockdown,

Table 2
The explanatory variable set (of independent variables actually used in final models).

Category	Variable code	Range[a]	Description
General	G1	[0,1]	Residency in the metropolitan area of Milan (0 = no, 1 = yes)
	G2	[0,1]	Gender (0 = women, 1 = men)
	G3	[1,7]	Age
	G7	[1,7]	The desire to change lifestyle
	G9	[1,7]	Health condition (self-reported)
	G12	[1,5]	Enjoyment of smart working or studying
Transport	T1	[1,4]	Area of movement within or outside of the metropolitan area of Milan
	T5	[1,6]	Possession/availability of means of transport
	T6	[1,4]	Preference for daily travel after L-D
	T7	[1,4]	Duration of daily travel before L-D
	T8	[1,4]	Purpose of daily travel before L-D
	T9	[1,5]	Satisfaction with public transport
	T11	[1,5]	Worry about using public transport
	T12	[1,5]	Information-seeking about public transport
Personality	P1	[1,7]	Extraversion
	P2	[1,7]	Agreeableness
	P3	[1,7]	Conscientiousness
	P4	[1,7]	Emotional stability
	P5	[1,7]	Openness to experiences

[a] To see the description of the variables please refer to Table 1.

improvements of personal life during lockdown, the desire to change lifestyle, and the amount of time spent every day to contact friends and family are also collected.

Moreover, related to daily travel behaviour, the respondents were asked to specify their area of movement, the mode of transport before, during, and after lockdown, possession or availability of any mode of transport, the preference for daily travel after lockdown, the duration, and purpose of daily travel, satisfaction with public transport. Also, the degree of worry about using public transport (in the presence of COVID-19), and information-seeking about public transport are asked. Finally, some information regarding personality traits (based on Big-Five personality traits on a seven-point Likert scale) was collected (Gosling et al., 2003).

In order to evaluate model performance, the confusion matrix, the RMSE, the estimated dispersion, and the deviance of the fit of the output data are reported. The confusion matrix measures model performance in predicting output. It is made up of a square matrix with as many rows and columns as the output classes taken into account. In each of its cells, the numbers of matching results are then inserted. For example, if there are three ordered classes, the first row (class 1) reports, in the order, the number of corrected values of class 1, those predicted in class 2 and those predicted in class 3. The last two are incorrect predictions. The same is done for the other two rows/classes. Then, the total diagonal sum of the matrix can be compared with its total, giving the Accuracy; the row sum compared with the correct value of its class, gives the Precision; the column sum compared with the correct values of its class, gives the Recall. From these values, we can gather rather detailed information about model performance. Accuracy states the overall performance of the model; the higher, the better the model. Precision and Recall state the performance for each class, showing over-prediction and dispersion. The higher the values, the better the performance.

4. Results

Three models are developed to analyse the association between the choice of transport mode before, during, and after lockdown and explanatory variables (Table 2). The Multinomial regression model was used. Output classifies the users into three classes:

'A' private car,
'B' public transport,
'C' active modes of transport (bicycle, walking, electric scooter, etc.).

The model has used the relative odds ratio of private car and public transport versus active mode. The reason is that we are more interested to understand the factors that are associated with active mode versus other and to give insight into the possible and potential factors that could encourage the use of active mode in the local context of Milan. The relative odds consist of two eqs. (A vs C and B vs C). In all models, the significant variables were low-filtered by a p-value <0.05. Increasing the value of the variables can increase or decrease the log of the odds ratio. If the variables have positive coefficients, they increase the log of the odds ratio; whereas if they have a negative coefficient, they decrease it. Therefore, for the first eq. (A vs C), when the ratio increases, the relative odds of a user being in class A (private car) versus class C (active modes users) increases, instead, when the ratio decreases, the relative odds of a user being in class C versus class A increases. For the second equation, when the ratio increases, the relative odds of a user being in class B (public transport) versus class C (active modes users) increases. On the contrary, the decrease in ratio increases the relative odds of a user being in class C versus class B. A variable present in both equations with the same positive sign decreases the relative odds of a user being in class C, whereas if it has a negative sign, it increases the relative odds of a user being in class C.

4.1. The choice of transport mode before lockdown (CBL)

This model investigates the choice of transport mode before the lockdown. The analytical model (made up of two equations) is as follows:

$$ln\left(\frac{\pi_{\text{class A}}}{\pi_{\text{class C}}}\right) = 1.6856^*G_1 + 0.7313^*T_1 - 0.1538^*T_5 - 1.0476^*T_6 + 0.4009^*T_7 + 0.1132^*T_8 - 0.431^*T_9 \tag{3}$$

$$ln\left(\frac{\pi_{\text{class B}}}{\pi_{\text{class C}}}\right) = -3.1663 + 1.2974^*G_1 + 0.4163^*T_1 - 0.2292^*T_5 + 0.9033^*T_7 + 0.1162^*T_8 + 0.6769^*T_9 \tag{4}$$

Fig. 1 shows the confusion matrix for the multinomial regression model. The accuracy is equal to 75 % and the precision and recall indices are presented in the figure for each class; Table 3 reports the statistical performance indices of the model. Model accuracy can be acceptable but it must be considered that performance of Active modes class is rather poor.

The effect of a unitary change on the output for all variables is shown in Fig. 2, and it is discussed hereafter.

In the first equation, we can observe that '*The residency in the metropolitan area of Milan*' (G1), '*Area of movement within or outside of the metropolitan area of Milan*' (T1) and, '*Duration of daily travel before lockdown*' (T7) increase the relative odds to be in the class of private car users (A) versus active mode users (C). As the movement of people for their daily travel included a wider area (also outside the metropolitan area of Milan), the probability that they used private car and public transport increased. For instance, it was (exp (0.7313)) 2.1 times more likely to use private car than active modes. Regarding the explanatory variable of '*The residency in the metropolitan area of Milan*' (G1), people who were not living inside the metropolitan area were 5.4 times more likely to use private car. For '*The purpose of daily travel*' (T8), we can argue that multi-purpose daily travels were 1.1 times less likely to be done by private cars than daily travels for work purposes. The '*Preference for daily travel after L-D*' (T6) is negatively related to class A. This variable decreased the probability (1 / exp (−1.05)) 2.9 times for private car users versus active mode users.

From the second equation, among variables with positive values of coefficients, the most significant effect is still '*The residency in the metropolitan area of Milan*' (G1): given all else equal, an increase of this

	Recall	66%	80%	37%	
True Class	private car A	171	82	5	66%
True Class	public transport B	68	594	7	89%
True Class	active modes C	21	70	7	7%
		private car A	public transport B	active modes C	Precision
		Predicted Class			

Fig. 1. Confusion matrix for choice of transport mode before lockdown.

Table 3
Statistical performance of the model for choice of transport mode before lockdown.

RMSE	Estimated dispersion	Deviance of the fit	Accuracy
0.3915	1.0246	1.1998e+03	0.7551

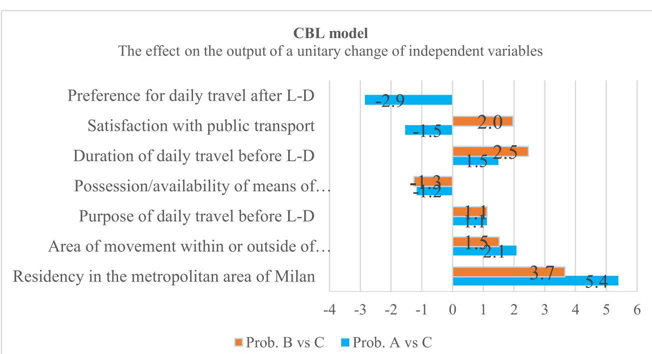

Fig. 2. Marginal effects (*) for CBL models.
(*) the values refer to how many times output increases (+) or decreases (−) when input variable has a unitary increase.

variable (from 0 to 1) implies an increase of the output of 3.7 times. This means that by increasing it, the relative odds of a user being in class B versus class C increases. '*The purpose of daily travel*' (T8), was positively related to the model, meaning that multipurpose daily travels were 1.1 times more likely to be done by public transport than daily travels for work purposes. '*Duration of daily travel before lockdown*' (T7) increases the relative odds to be in the class of public transport users (B) versus active mode users (C). Therefore, longer travel time increases the likelihood of using public transport versus active mode of transport 2.5 times, given all else is equal. Other variables are positively related to the second equation of the model.

4.2. The choice of transport mode during lockdown (CDL)

This model investigates the choice of transport mode used during the lockdown.

$$ln\left(\frac{\pi_{\text{class A}}}{\pi_{\text{class C}}}\right) = 0.553^*G_2 + 0.1889^*G_9 + 0.5924^*T_1 + 0.0946^*T_5 - 0.4565^*T_6 - 0.0786^*T_8 - 0.1953^*T_9 \quad (5)$$

$$ln\left(\frac{\pi_{\text{class B}}}{\pi_{\text{class C}}}\right) = 1.153^*G_1 - 0.3856^*G_{12} + 0.3656^*T_7 + 0.4987^*T_6 - 0.3757^*T_{11} - 0.3286^*P_2 \quad (6)$$

The confusion matrix for the multinomial regression model is presented in Fig. 3. The accuracy is equal to 74 % and the precision and recall indices are reported in Fig. 3 for each class. Fig. 4 shows the marginal effects of variables, and Table 4 reports the statistical performance of the indices of the model.

The variables show both positive and negative effects on the choice of mode of transport during lockdown. In the first equation, among negative values of coefficients, the most significant effect is given by '*Preference for daily travel after lockdown*' (T6). It means that, given all else equal, a unitary increase of this variable implies a decrease of the output of 1.6 times. '*Area of movement within or outside of the metropolitan area of Milan*' (T1) gives the highest positive effects. Given all else equal, a unitary increase implies an increase of the output of 1.8 times.

Moreover, in the second equation among negative values of coefficients, the most significant effect is given by '*Enjoyment of smart working or studying*' (G12). It means that a unitary increase in this variable implies a decrease of the output of 1.5 times. '*Residency in the metropolitan area of Milan*' (G1) gives the highest positive effect equal to 3.2 times. Only '*Preference for daily travel after lockdown*' (T6), is present in both equations with opposite signs. This means that when T6 increases, the probability to choose B (π_B) increases over the probability to choose C (π_C) which increases over the probability to choose A (π_A), and then π_B increases much more over π_A. The effect of a unitary change on the output for all variables is shown in Fig. 4.

4.3. The choice of transport mode after lockdown (CAL)

This model investigates the choice of transport mode after the lockdown. Similar to the previous models, a multinomial nominal regression is used. The analytical model is as follows.

$$ln\left(\frac{\pi_{\text{class A}}}{\pi_{\text{class C}}}\right) = 0.3959^*G_2 - 0.109^*G_7 + 0.643^*T_1 - 0.1544^*T_5 - 0.9707^*T_6 + 0.238^*T_{11} - 0.1462^*P_5 \quad (7)$$

$$ln\left(\frac{\pi_{\text{class B}}}{\pi_{\text{class C}}}\right) = -3.2593 + 0.3759^*G_3 - 0.1498^*T_5 + 0.5967^*T_6 + 0.4111^*T_7 - 0.2421^*T_{11} + 0.2296^*T_{12} - 0.2531^*P_5 \quad (8)$$

The confusion matrix for the multinomial regression model is presented in Fig. 5. The accuracy is 66 % and the precision and recall indices are presented in Fig. 5 for each class, and Table 5 demonstrates the statistical performance indices of the model. For this model, performance is better distributed among classes.

Considering the marginal effect of variables, in the first equation, among negative values of coefficients, the most significant effect is given by '*Preference for daily travel after lockdown*' (T6). It means that given all else equal, a unitary increase implies a decrease of the output of 2.6 times. '*Area of movement within or outside of the metropolitan area of Milan*' (T1) gives the highest positive effects. Given all else equal, a

	Recall	77%	47%	41%	
True Class	private car A	719	11	13	97%
True Class	public transport B	62	21	14	22%
True Class	active modes C	153	13	19	10%
		private car A	public transport B	active modes C	Precision
		Predicted Class			

Fig. 3. Confusion matrix for multinomial regression model of choice of transport mode during lockdown.

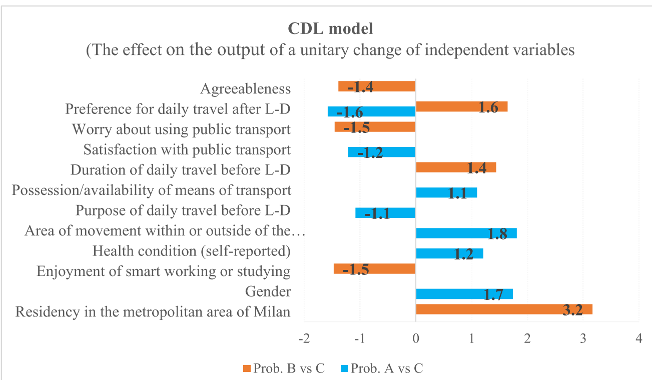

Fig. 4. Marginal effects (*) for CDL models.
(*) the values refer to how many times output increases (+) or decreases (−) when input variable has a unitary increase.

Table 4
Statistical results of regression analysis of the choice of transport mode during lockdown.

RMSE	Estimated dispersion	Deviance of the fit	Accuracy
0.2826, 0.4254	1.0725	1.2509e+03	0.7405

unitary increase implies an increase of the output of 1.9 times. '*Gender*' (G2) was also related to the first equation concerning the private car users. The results show that shifting from women (0) to men (1) increases the probability of class A versus class C. Indicating that men compared with women are more likely (1.5 times) to use a private car rather than an active mode of transport.

Also, in the second equation, the variables show both positive and negative effects. Among negative coefficients, the most significant effect is given by '*Personality (openness to experiences)*' (P5). It means that given all else equal, a unitary increase implies a decrease of the output of 1.3 times. '*Preference for daily travel after lockdown*' (T6) gives the highest positive effects: given all else equal, a unitary increase implies an increase of the output of 1.8 times. '*Age*' (G3) was also related to the second equation concerning public transport users (Fig. 6).

Among significant variables, T11, '*Worry about using public transport*' (T11) is present in both equations with opposite signs (+/−). This implies that when T11 increases π_A increases over π_C which in turn increases over π_B, and then π_A increases much more over π_B. Also, '*Preference for daily travel after lockdown*' (T6) is present in both equations with opposite signs (but with the sequence −/+). This shows that when T6 increases, π_B increases over π_C which in turn increases over π_A, then π_B increases much more over π_A.

Fig. 7 shows the role of T6, '*Preference for daily travel after lockdown*' (T6) which is present in the first equation with a negative sign and the second equation with a positive sign. The probability of class 'A' versus class 'C' (Fig. 7a) decreased as the preference for daily travel of respondents shifted towards public transport. On the contrary, the probability of class 'B' versus class 'C' (Fig. 7b) increases with T6.

4.4. The CBL, CDL, CAL models with normalised data

In this study, further, we modelled the regressions also by normalised variables in the range [0,1]. These models allow us to evaluate the overall importance of independent variables by comparing their coefficients directly. However, we must add that the normalised model is by definition out of scale. It only considers the dynamics of a variable inside its range and the contribution of each variable is summed to calculate the log value. The coefficients and p-values are reported in Table 6.

Table 5
Statistical results of the regression model of the choice of transport mode after lockdown.

RMSE	Estimated dispersion	Deviance of the fit	Accuracy
0.2015, 0.2743	1.0547	1.5704e+03	0.6644

	Recall	69%	60%	65%	
True Class	private car A	327	15	95	75%
True Class	public transport B	40	60	60	38%
True Class	active modes C	109	25	294	69%
		private car A	public transport B	active modes C	precision
		Predicted class			

Fig. 5. Confusion matrix for multinomial regression model of the choice of transport mode after lockdown.

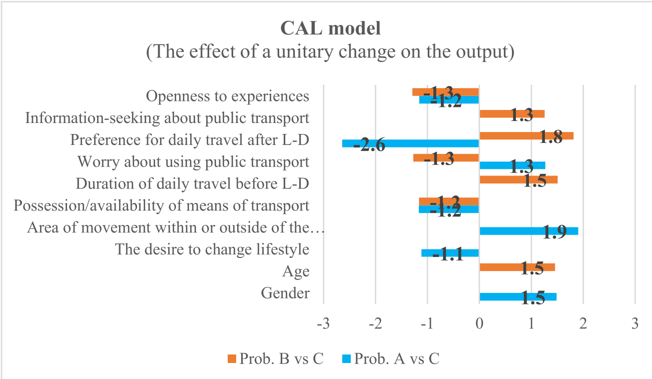

Fig. 6. Marginal effects (*) for CAL models.
(*) the values refer to how many times output increases (+) or decreases (−) when the input variable has a unitary increase.

Firstly, in the normalised CBL model, the significance of the *Duration of daily travel before the lockdown* (T7) was lower (in absolute value) than the *Satisfaction with public transport* (T9). In other words, *Duration of daily travel before lockdown* (T7) increased the probability of public transport users 2 times versus active mode. However, *Satisfaction with public transport* (T9) increased the likelihood of public transport users by 3.3 times versus active mode. So, the normalised model gives us the insight that the explanatory variable of *Satisfaction with public transport* (T9) has a greater influence on class B for their choice of transport mode before lockdown rather than *Duration of daily travel before lockdown* (T7).

The second normalised model (CDL) shows two factors *Worry about using public transport* (T11) and *Agreeableness* (P2) decreased the probability of class B by 1.3 and 2 times versus class C. This implies that the influence of the personality trait of agreeableness on public transport users was more significant compared with *Worry about using public transport* (T11) on the choice of transport mode during the lockdown.

Lastly, from the normalised model of CAL, we find that *Openness to experiences* (P5) decreased the probability of public transport users 1.5 times, and *Worry about using public transport* (T11) decreased the probability of this class by 1 times versus active mode. On the contrary, *Age* (G3) significantly increases the probability of choice of public transport. The data reveals that the personality trait of *Openness to experiences* (P5) had more influence on the choice of transport mode after lockdown rather than the *Worry about using public transport* (T11).Table 6:

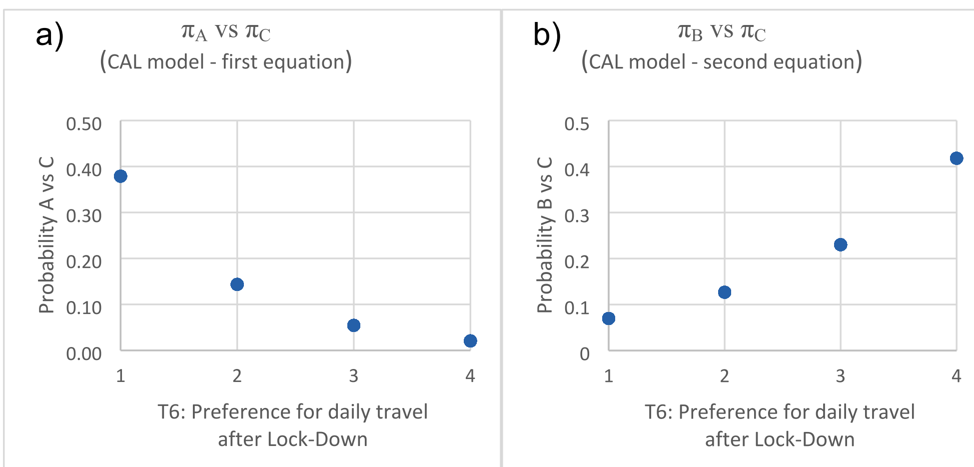

Fig. 7. The figure on the left shows the probability of class A versus the probability of class C and the figure on the right shows the probability of class B versus the probability of class C for *Preference for daily travel after lockdown* (T6).

Table 6
Independent variables and p-value for the three transport choice models with normalised data.

Code	Model					
	CBL		CDL		CAL	
	A vs C	B vs C	A vs C	B vs C	A vs C	B vs C
Intercept 1	–	−1.4791*	–	–	–	−2.3838**
G1	1.6564**	1.1821**	–	1.0398*	–	–
G2	–	–	0.5805*	−0.1734*	0.3796*	–
G3	–	–	–	–	–	2.3475**
G7	–	–	–	–	−0.6185*	–
G9	–	–	1.1731*	–	–	–
G12	–	–	–	−1.2505*	–	–
T1	2.3011**	1.3574*	1.831**	1.3305*	1.9647**	–
T5	−1.2305*	−1.7362**	0.7426*	–	−1.2075**	−1.1435**
T6	−2.9184**	–	−1.232**	1.7593**	−2.7998**	1.8325**
T7	0.9413*	2.0481**	–	–	–	0.9666*
T8	0.7466*	0.7599*	−0.5127*	–	–	–
T9	−2.2272**	3.2970**	−1.0835*	–	–	–
T11	–	–	–	−1.2919*	0.962**	−1.0015*
T12	–	–	–	–	–	0.9185*
P2	–	–	–	−2.0191*	–	–
P5	–	–	–	–	−0.9091*	−1.5460*

Legend: minus sign – means a non-significant variable, one-star * means $p < 0.05$, two stars ** mean $p < 0.001$.

Independent variables and p-value for the three transport choice models with normalised data.

5. Discussion

In the following, we discuss the three models and review the significant explanatory variables related to the transport mode before, during, and after the pandemic (Table 7). The similarities and differences of the common variables are discussed to understand the impact of COVID-19 lockdown on the travel mode choice behaviour of respondents in the above-mentioned phases. Finally, the research hypotheses, potentials, limitations, and future research are addressed.

5.1. CBL, CDL, CAL models: similarities and differences

Considering the three models of CBL, CDL, and CAL, we found that people who were residing outside Milan and had to commute to their work or other activities to the metropolitan area were, respectively, 5.4, and 3.7 times more likely to commute by private car and public transport versus active mode of transport. These results, as expected, are in line with prior studies (Ashrafi & Neumann, 2017; Both et al., 2022; Cheng et al., 2019; De Vos et al., 2022; Yu et al., 2019). In the second model, related to the choice of transport mode during the lockdown, these explanatory variables show a different relation. For instance, the residents outside the metropolitan area were 3.2 times more likely to use public transport versus active modes. Similar values show that residency played the same role for people who were not living in Milan, and they chose public transport over active transport mode even during the lockdown. Similarly, previous findings have also highlighted that the use of a private car has remained the same, especially in rural areas during the pandemic (Brezina et al., 2021).

In this study, the transport mode before the lockdown is related to the area of movement and duration of travel. So, people who travel a wider area (inside and outside the metropolitan area) are 2.1, and 1.5 times more probable to use a private car and public transport, respectively, rather than active modes. In the CBL model, he area of movement during lockdown is related to private car users (class A) with a significance of 1.8 times (see Eq. (5)). This factor increased the probability of the CDL model 1.9 times similarly (Eq. (7)).

The possession/availability of means of transport is positively related to the transport mode before the lockdown. Classes A and B are (1.2, and 1.3) less likely to have access to other means of transport such as a bicycle. Many studies have also indicated that providing or easing access to other means of transport such as active mobility can positively increase the use of active modes (Ton et al., 2019). During the lockdown, people who accessed a private car were (1.1 times) more likely to use it for their daily travels (Eq. (1)). However, we can see that both classes of private car and public transport users predicted that they would be (1.1 times) less likely to use other means of transport compared to a private car after the pandemic. In other words, they were willing to use private

Table 7
Independent variables and p-value for the three transport choice models.

Category	Variable code	Description	CBL		CDL		CAL	
			Choice		Choice		Choice	
			Before		During		After	
			A vs C	B vs C	A vs C	B vs C	A vs C	B vs C
		Intercept 1	–	** ▲	–	–	–	** ▲
G	G1	Residency in the metropolitan area of Milan	** ▼	* ▼	–	* ▼	–	–
	G2	Gender	–	–	* ▼		* ▼	–
	G3	Age	–	–	–	–	–	** ▼
	G7	The desire to change lifestyle	–	–	–	–	* ▲	–
	G9	Health condition (self-reported)	–	–	* ▼	–	–	–
	G12	Enjoyment of smart working or studying	–	–	–	* ▲	–	–
T	T1	Area of movement within or outside of the metropolitan area of Milan	** ▼	* ▼	** ▼	–	** ▼	–
	T5	Possession/availability of means of transport	* ▲	** ▲	* ▼	–	** ▲	** ▲
	T6	Preference for daily travel after L-D	** ▲	–	** ▲	** ▼	** ▲	** ▼
	T7	Duration of daily travel before L-D	* ▼	** ▼	–	* ▼	–	** ▼
	T8	Purpose of daily travel before L-D	* ▼	* ▼	* ▲	–	–	–
	T9	Satisfaction with public transport	** ▲	** ▼	* ▲	–	–	–
	T11	Worry about using public transport	–	–	–	* ▲	** ▼	* ▲
	T12	Information-seeking about public transport	–	–	–	–	–	* ▼
P	P2	Personality trait of Agreeableness	–	–	–	* ▲	–	–
	P5	Personality trait of Openness to experiences	–	–	–	–	* ▲	* ▲

Legend: Variables on rows and models in column and p-values inside; the up arrow ▼ indicates a positive coefficient, the down arrow ▲ a negative one; a minus sign – means a non-significant variable, one-star * means $p < 0.05$, two stars ** mean $p < 0.001$; na = not applicable, L-D = lockdown.

cars more than bicycles and scooters after the lockdown.

In line with previous findings (Van Lierop et al., 2018), the model before lockdown represents that satisfaction with public transport is adversely related to private car users (equal to 1.5 times), while public transport users are (2 times) more probable to be satisfied with public transport versus active mode users. The satisfaction with the public transport of private car users during the lockdown is negatively associated (1.2 times) with the model (Eq. (3)).

Furthermore, for models during and after the lockdown, preferences show a notable association with the choice of transport mode. During the lockdown, class B is (1.6 times) more likely than active modes (class C). Besides, class A is (1.6 times) less likely than active modest. The influence of the preferences on the modal choice after the lockdown for classes A and B is equal to 2.6 and 1.8 times, respectively. This explanatory variable showed that the people's preferences for daily travel after the lockdown are negatively related to the CBL model, indicating that class A is 2.9 times less likely than class B (public transport). These results are interesting as they show public transport users are more interested to use active mode after the lockdown, and, as discussed before, it could be due to the change in lifestyle with flexible smart working and negative perceptions due to covid-19. Besides, In line with Gnerre et al. (2022) findings, satisfaction with public transport (T9) was positively (and less significantly) associated with private car users, meaning that higher satisfaction with public transport increased the probability of private car users considering the active mode of transport mode during the pandemic.

Among socio-demographic variables, gender has a considerable effect on transport mode during and after lockdown. The significance of the effect for private car users is equal to 1.7, and 1.5 times, respectively. In other words, men compared with women are more likely to use a private car versus active modes of transport, and, similarly, women are more likely to use active modes of transport such as cycling, and walking than using a private car. Despite the findings of Campisi et al. (2020), the model shows that women are less likely to use the private car versus active modes during the pandemic which is similar to the findings of Scorrano and Danielis (2021).

Besides, the age of the respondents is related to the choice of transport mode after the lockdown. The positive relationship with public transport users shows that older people are (1.5 times) more likely to use public transport after lockdown meaning that older adults preferred using public transport after the pandemic and younger adults preferred using active mode versus public transport that could be due to the better accessibility of public transport for older people in the city (Dadashzadeh et al., 2022; Guida & Carpentieri, 2021). It is noteworthy that the survey was carried out when people were still under the stay-at-home measure (lockdown) and the modal choice after lockdown represents their preferences and interests for their daily travel after lockdown. This argument, as discussed before in the literature review, is closely related to preferences and attitudes (de Haas et al., 2020). Therefore, here we can say that older adults compared with younger people had the preference and desire to use public transport versus active modes of transport after the lockdown.

Worrying about using public transport is related to the transport mode during and after the lockdown. Results show that the feeling of worry decreased the likelihood of using public transport (equal to 1.5 times) during the lockdown. Similarly, the feeling of worry is associated with transport mode after the lockdown. The probability of using a private car increased by 1.3 times and the using public transport decreased by 1.3 times versus active modes. This is in congruence with many studies during the pandemic (Abdullah et al., 2020; Abdullah et al., 2021; Abdullah et al., 2022; Chen et al., 2021; Chen et al., 2022; Cusack, 2021; Das et al., 2021; Dingil & Esztergár-Kiss, 2021; Echaniz et al., 2021; Nikiforiadis et al., 2020; Schaefer et al., 2021; Shakibaei et al., 2021; Shibayama et al., 2021; Zafri et al., 2022).

The variables of the degree of enjoyment with smart-working/studying and the personality trait of agreeableness are related to the choice of transport mode during the lockdown. Concerning the activities that people were engaged with during the lockdown. We asked them how much they like this activity during the pandemic, and only 20 % did not give us positive feedback. Therefore, it is assumed that this activity was positively integrated with people (Bolisani et al., 2020). The results of the CDL model show that the likelihood of using public transport decreased (1.5 times) as the degree of enjoyment with smart-working/studying was higher. Further, regarding personality traits, the model indicates that people with a higher degree of agreeableness are (1.4 times) less likely to use public transport than active modes. Agreeable individuals tend to be friendly, cooperative, adaptable and less competitive. Some recent findings also have emphasised that due to prosocial behaviour, and altruism in agreeable individuals they are more probable to use active and shared modes (Malichova & Tokarcikova, 2021).

Finally, three factors are related to the CAL model. Firstly, information-seeking about public transport positively influenced public transport users (1.3 times) versus active modes. It shows that public transport users liked to acquire some information about the timing and availability of vehicles. Secondly, class A is less likely to have a higher degree in the desire to change lifestyle. Lastly, the personality trait of openness to experiences showed a negative association with both classes A and B. It indicates that a higher degree of openness to experiences reduced the likelihood 1.2, and, 1.3 times, respectively for private (class A) and public transport (class B) users. The results are consistent with recent findings (Roos et al., 2022). People who are highly open to new experiences appreciate the novelty and variety in experiences, they are open to innovations, and different cultures which may encourage them to use various modes and have the desire to use also active mode after the pandemic.

We also compared our results of the transport mode after lockdown with real data to understand the accuracy of the model predictions. The choice of transport mode before, during, and after the lockdown based on the data of the current study is presented in Fig. 8. It demonstrates that mostly the use of public transport would decline after the lockdown. It is evident that private car (auto) use and walking would experience a sharp fall, while the use of the metro as public transport could grow gradually.

Besides, Fig. 9 shows the usage change rate of different modes of transport in 2020 in Milan. This figure is very detailed and it also shows minor fluctuations of the movements in the choices. However, we are interested in the overall changes of the transport mode choices before and After the May of 2020, since our survey was carried out in May.

Besides, Fig. 9 shows the usage change rate of different modes of transport in 2020 in Milan provided by a regional agency (Assolombarda, 2021). This figure is very detailed and it also shows minor fluctuations of the movements in the choices. However, we are

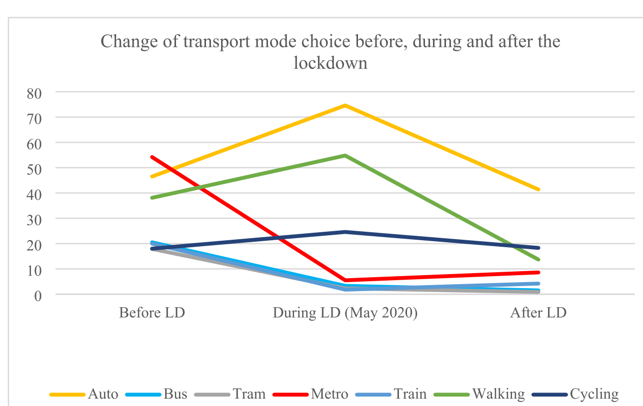

Fig. 8. The choice of transport mode before, during, and after the lockdown (current research) (note that Bus, Tram, and Train modes are overlapping).

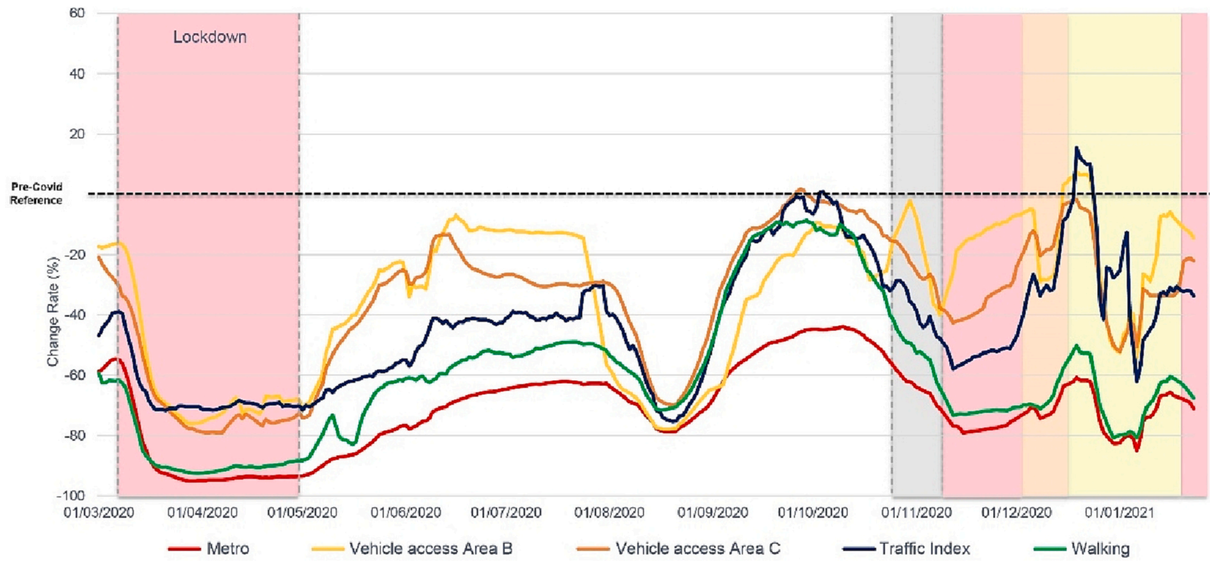

Fig. 9. The usage change rate of different modes of transport over year 2020 in Milan.
(Retrieved and adapted from Assolombarda.)

interested in the overall changes of the transport mode choices before and after May 2020, when our survey was carried out.

As it is depicted in Fig. 9, initial restrictions were lifted around May 2020 and it is exactly when respondents were asked to choose the transport mode that they would prefer to use after the lockdown. Based on real statistics, the use of all transport modes after the lockdown experienced several fluctuations. After the lockdown, a considerable decline in the use of a private car which then it has increased and tended to rebound. Whereas, metro use increased steadily and gradually after the lockdown. Walking remained steady for some time and then it started to increase.

Therefore, the comparison between the two Figs. 8 and 9 shows that the preference for using transport modes after the lockdown is interestingly similar for the metro and a private car for a short period. As both figures indicate a decline in private car use and a slight increase in metro use. The only difference is that the respondents of this study tended to walk less after the lockdown which could be seen as the steadiness of walking for a very short period. However, we can indicate that the only difference between real and predicated data is concerned with the active mode of walking.

5.2. Research hypotheses, limitations, and future work

In this research, firstly, we demonstrated that there are several individual characteristics (e.g., socio-demographics, and personality traits of Agreeableness and Openness) and daily travel are related to the choice of transport mode during, and after the first lockdown (see Table 7). Also, we presented some individual factors (such as age, gender, personality traits) are more relevant to the choice of transport mode during and after the pandemic while some of them were not associated with transport mode before the pandemic. Overall, this research tried to shed light on the parameters and factors that influenced the change of travelling choices. Also, the findings regarding future mode preferences due to the lockdown are presented.

However, the findings of this study have to be seen in the light of some limitations. In this research, we only could collect data during the first lockdown and further access to the same participants during other lockdowns was not possible. The study of the same group of people during other lockdowns could show the effect of individual factors on the modal choice of other episodes of quarantine which could provide more information about the behavioural changes in the choice of transport mode in the longer term. Also, our questions were mostly related to the main travel attributes during the lockdown. Our survey questions covered the most influential personal and travel factors. Considering micro mobility and other relevant characteristics of active travel mode could provide us a better insight to the travel mode choice during and after lockdown. Lastly, the population sample of this study was mostly employees and students in Milan, although the sample resemble similarities to the real population of Milan (as discussed before), the results cannot be generalised to the whole population as people who did not have access to Internet were excluded from the survey.

Future research needs to consider the role of both individual and travel characteristics (e.g., personal characteristics, preferences, and personality traits) in changes in daily travel behaviour during extraordinary situations and pandemics. It is also suggested that future research study the relevance of micro mobility modes (such as bicycles and scooters) with the choice of active travel modes by considering individual (e.g., personalities) and travel characteristics. We observed that the significance of the influence of these factors was different before, during, and after the lockdown. Observed relevant factors can also help to predict future transport mode behaviour that could consequently provide valuable recommendations for policy-making during similar lockdowns in future. Besides, it would also offer more efficient policies for the transport system and adapt better to sudden occasions such as the COVID-19 pandemic that are closely linked to topics of sustainable and resilient transport systems.

6. Conclusions

In this study we identified which personal and travel characteristics are associated with the choice of transport mode before, during, and after the lockdown. A survey was carried out in the spring 2020 in Milan, and, based on the collected data, three multinomial regression models (MNR) are applied. The results show that residency, area of movement, and the duration of travel are significantly associated with the choice of transport mode before the lockdown. However, the significance of these variables varied for the choice of transport mode during and after the lockdown. Moreover, socio-demographic variables (such as gender and age), preferences for daily travel, and negative feelings of worry about using public transport are associated with the choice of transport mode during and after the lockdown. For instance, gender has a considerable effect on transport mode during and after lockdown. Meaning that men compared with women are more likely to use the private car versus active modes of transport, and women are more likely to use active modes of transport such as bicycle rather than private car. Finally, activity-related factors such as enjoyment of smart-working/studying, information seeking about public transport, and personality traits of agreeableness and openness to experiences, respectively, are related to the choice of transport mode during and after the lockdown.

CRediT authorship contribution statement

Lorenzo Mussone: Conceptualization, Methodology, Software, Writing, Reviewing and Editing
Farzaneh Changizi: Conceptualization, Methodology, Literature review, Writing, Reviewing and 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.

Data availability

Data will be made available on request.

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