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Understanding the impact of COVID-19 on travel mode choices and predicting the modal shift after the pandemic

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ABSTRACT

During the COVID-19 pandemic, the measures taken by authorities to contain the virus and the fear of being infected resulted in reduced human mobility. Even though studies have made an effort to understand the changes in human mobility patterns resulted due to the pandemic, their findings are inconclusive for totally relying on aggregated data collected at ridership level rather than information at the individual-level. Our study uses four waves of travel survey data collected before, during and after the COVID-19 pandemic, in Montreal, to assess the determinants of mode choice and to analyse changes in travel behavior and mode choices. We had 2933 work-related trips from 1275 participants, of which only 290 participants responding in both wave 1 and wave 4 qualified for the mode prediction analysis. We applied a multinominal multilevel analysis to explore predictors of travel behaviour, and a classical multinominal model to analyse mode choice change. Our study's findings show a huge decline in public transit use during COVID-19 and that it gradually increased after COVID-19, even though it was not comparable to the pre-pandemic level. The odds of public transit users shifting back to public transit after the pandemic was 22.54 (95%CI: 7.29, 69.66) times higher than choosing private motorized vehicles, while the rebound of active transport users was relatively higher (OR: 52.71, 95%CI: 8.68, 320.20). Our study implies that not all the sustainable mode users have returned to using the modes after COVID-19, and it stands as a challenge for transport authorities to develop appropriate strategies to encourage them to rebound.

1. Introduction

The outbreak of the Coronavirus disease 2019 (COVID-19) was declared a pandemic by the World Health Organization on the 11th of March 2020 (Echaniz et al., 2021). Several measures taken by authorities to contain the virus, such as lockdowns, social distancing, canceling public events, school closures, public transport closures, travel restrictions, and the possibility of teleworking for different professionals, dramatically changed people's travel behavior as well as their travel mode choices.

Various studies demonstrated the reduction in overall daily mobility during the pandemic (Aloi et al., 2020; Politis et al., 2021; Shamshiripour et al., 2020), with a dramatic reduction in public transit use (De Vos, 2020; Shamshiripour et al., 2020), and a shift from shared travel mode to private modes (Abdullah et al., 2020; Schaefer et al., 2021). In Canada, overall traveling dropped by about 52 % during the COVID-19 pandemic (Fatmi, 2020), and public transit ridership reduced by 46 % in Montreal, 42 % in Vancouver, and 59 % in Toronto between 2016 and 2021 (Negm and El-Geneidy, 2024). In Toronto, regular transit commuters changed their habits mostly by adopting one of three traveling options during the pandemic: strictly driving cars, walking, or continuing transit with a high preference for walking (Loa et al., 2021). Several other studies conducted globally have also suggested a decrease in public transit use and an increase in car dependency (Jenelius and Cebecauer, 2020; Kim et al., 2021; Park, 2020) and active transport mode (walking and biking) during the pandemic (Nikiforiadis et al., 2020; Schaefer et al., 2021).

During the pandemic, shifts in travel modes were linked to differential perceptions of infection risk by travel mode; high-contact modes like public transit tended to be avoided (Abdullah et al., 2020; Barbieri et al., 2021; Eisenmann et al., 2021). Another likely explanation for that shift in transport modes as well as reduction in mobility would be the

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possibility of online education and smart (teleworking) work systems because of the reinforcement of social distancing (Belzunegui-Eraso and Erro-Garcés, 2020; Okubo, 2022).

1.1. Literature review

COVID-19 pandemic has disturbed people's mobility patterns and resulted in a new order for all behaviors past the pandemic. This might be the reflection of high levels of stress, depression, and anxiety caused by the pandemic (Passavanti et al., 2021). While the risk of infection and its consequences have leveled off, changes in work habits – e.g. mainly telework – seem to endure, meaning mobility behaviors adopted during the pandemic tend to be maintained (Cui et al., 2020), indicating that private car use and active transport will be at the optimal even after the pandemic is over (Nikiforiadis et al., 2020; Rodríguez González et al., 2021; Thomas et al., 2021). Likewise, a Greek survey (2020) reported that pre-pandemic active travelers were more likely to continue commuting via active modes post-pandemic, with some car users interested in switching their main mode to active transport (Nikiforiadis et al., 2020). On the contrary, a UK survey conducted in April 2020 documented that most car commuters would return to using cars (81.9 %), while only 2.6 % and 6.5 % of them might switch to walking and cycling, respectively, after the travel restrictions are lifted (Harrington and Hadjiconstantinou, 2022). Meanwhile, the study also reported that people's intention to return to using the same mode for work trips after COVID-19 found that of the initial transit users, 51 % would stick to the same mode, while 49 % might possibly switch to other modes (i.e., 9 %, 11.5 %, and 28.5 % would shift to walking, cycling, and driving cars, respectively) (Harrington and Hadjiconstantinou, 2022). Another study in New Zealand and Australia also found that regular public transit users showed positive attitudes towards using the same mode once the pandemic is over (Thomas et al., 2021). Furthermore, a Polish study conducted in 2020 found that about 75 % of public transit users were willing to go back to using the same mode when the epidemic is over (Przybylowski et al., 2021). Likewise, in 2021, only 68 % of pre-pandemic transit riders in a Canadian city thought of shifting back to using transits (Palm et al., 2022). Furthermore, a survey from ten countries found that even though the use of public transit did not go back to the level before the pandemic, there was a remarkable increase in its use after the pandemic (Monterde-i-Bort et al., 2022). Meanwhile, the study also suggested that using private cars and walking returned to normal, while cycling was the only mode not affected by the pandemic (Monterde-i-Bort et al., 2022). About 80 % of Canadians who started teleworking during the pandemic reported that they would probably continue telecommuting post-pandemic (Palm et al., 2022), which would hamper the use of all modes for work-trips proportionately. While public transit hasn't bounced back, the use of private motorized vehicles has almost recovered compared to pre-pandemic levels (Melo, 2022).

Even though findings from the past studies are enriching, most studies about changes in mode choice before and after the pandemic did not use any objective measures beyond 2022, and a large number of studies actually relied on pandemic-period surveys asking which mode of transport people would prefer to use once the pandemic is over. But the response to that question does not tell us much – as it is biased by the prevailing fear of the ongoing COVID-19 infection (Borkowski et al., 2021). This results in a probably inflated portion of respondents declaring preferring an unshared mode of transportation (private car or active transport) rather than public transit (Abu-Rayash and Dincer, 2020). Another limitation of past studies is the use of public transit ridership or vehicle density to represent trip demands during different pandemic phases. Such aggregated count-based trip data do not represent the travel behavior observed at an individual level. Moreover, travel habits, like other habits, are hard to change. People who repeat the same journey under similar circumstances tend to stick to the same travel mode rather than explore alternatives (Verplanken et al., 1994). Therefore, to better understand post-pandemic travel mode choices, it is crucial to consider pre-pandemic mode choices, and this has rarely been done to date using personal level data collected after 2022.

1.2. This current study

This work contributes to the existing literature in several ways. First, given the pandemic has disturbed people's mobility patterns and resulted in a new order for all behaviors, the influence of factors such as individual, trip, and built environment characteristics on transport mode choices need to be re-visited. Specifically, this work focuses on predicting the tendencies of sticking to the same or shifting to different transport modes in post-pandemic (2023) periods based on transport modes used in the pre-pandemic (2019) phase. To the best of our knowledge, this has not yet been explored in any past study, using data collected beyond 2022. Therefore, we believe that this clear assessment of the public's preferred transport modes after the pandemic might serve as a guide for the new transport policy. Additionally, this work analyses the shifting of transport modes from private motorized vehicles to walking, cycling, or public transit in the post-pandemic scenario, considering the fact that authorities worldwide have been encouraging people to use greener alternatives to transport modes than cars (Pan-European Programme, 2014). We focused only on work-related trips since these were more often maintained during the COVID-19 pandemic than schools and non-essential trips. These trips are also interesting because of their habit-forming nature, being made at the same time of the day with fixed start and end points. Additionally, working-class people often have more options in mode choice than older people or children. Thus, understanding the preferences of working individuals, who are the majority in the total population, in the post-pandemic period can represent an important scenario about mode preferences.

2. Methods

2.1. Data collection

The data for this study comes from the four-wave longitudinal online bilingual Montréal Mobility Survey administered in Greater Montreal, targeting people older than 18. The first wave of the survey, conducted between October and November of 2019, collected data from 3,520 participants, while the second wave in 2021 (October and November) had 4,058 valid responses. Likewise, the third wave and fourth were launched between October and November of 2022 and 2023 and had 4,065 and 5,312 valid responses. Various recruitment methods were used to increase sample diversity including distributing flyers, launching online advertisement campaigns, providing incentives to the participants, and hiring a public opinion survey company (Dillman et al., 2014). All participants who took part in one of the surveys and provided their email addresses were invited to participate in the follow-ups. This resulted in certain repeated measures across the four waves.

Exclusion criteria for the study included removing multiple responses entered with the same email or I.P. address, invalid age, height change across the waves, forms filled in the fastest 5 % response time, and those pinning their home/school/work address outside the study area. Surveys were conducted during the fall seasons. We retained participants who reported a valid work location and at least one work-related trip in the previous week and who had at least participated in two of the four waves, e.g. had provided repeated data. The same travel behaviour questions, such as mode choices for their recent travel to work and teleworking were used in all waves. Furthermore, longitudinal approach is the appropriate study design to unravel the authentic impact of built environment on mode choice (Bohte et al., 2009; Cao et al., 2009; Mokhtarian and Cao, 2008).

2.2. Data

2.2.1. Main transport mode

We classified the main transport mode used in recent home-to-work trip into three main categories: active transport (walking and cycling), private motorized transport (car, taxi, uber, rideshare, and motorbikes), and public transport (bus and train).

2.2.2. Built environment features

Walk Score® (Hall and Ram, 2018), a popular measure of walkability of the neighborhood, was retrieved for each individual's home location from Walkscore.com. These scores lie between 0 and 100, from "very car-dependent" (0 to 24), "car-dependent" (25 to 49), "walkable" (50 to 69), "very walkable" (70 to 89), to "walking paradise" (90 to 100).

The measure of job accessibility by public transport used in this study corresponds to a cumulative opportunities indicator for all jobs in the region using a 45-minute threshold (El-Geneidy and Levinson, 2022). The 45-minute threshold is selected because it is close to the Montréal region's median transit travel time, as recommended by Kapatsila et al. (Kapatsila et al., 2023). To calculate this indicator, transit travel times were computed between census tract (CT) centroids for a typical weekday between 8:00 and 9:00 AM using the "r5r" package (Pereira et al., 2021). CTs were chosen as the unit of analysis, as job data was obtained at this level from the 2016 census commute flows (Statistics Canada, 2018). The necessary inputs to calculate transit travel times were the Global Transit Feed Specification (GTFS) data and the OpenStreetMap (OSM) street network which were collected for each wave's year.

2.2.3. Residence self-selection

Residence self-selection (RSS) is important to consider, as it indicates if and how much built environment factors, themselves associated with travel mode choice, served as home location criteria. (Cao, 2015). Arguably, RSS significantly confounds the association between built environment and travel behavior (Chen et al., 2021; Manaugh and El-Geneidy, 2015). Ignoring it conflates the effect of built environment on mode choices (Ettema and Nieuwenhuis, 2017; Mokhtarian and Cao, 2008). We asked participants whether they gave importance to these characteristics while choosing a residential neighbourhood: walkability, being able to move around by car, being near bicycle infrastructure, being near public transportation, and the presence of parks and green spaces. These RSS features were assessed on a five-level Likert scale, ranging from "very important" to "very unimportant", and recategorized into two groups – "very important" and "important" were coded as "yes-important" and all other options were labelled as "not-important". All our models were adjusted for the above-mentioned RSS self-reports.

2.2.4. Trip related variables

We calculated car and transit duration for all home-office trips and divided them by 5 in order to convert these into 5-minute incremental units. Commuting travel times by car and transit were retrieved through the Google Maps API during the same week the survey response was collected. The travel time estimation process considers congestion and transit scheduling according to the day of the week and time of day of the respondent's last commute. We calculated the road distance between the work location and the nearest bus and train station and dichotomised it into less/more than 150 m and 500 m respectively. These distances were calculated using the "dodgr" R package (Padgham, 2019). The distance used in our study corresponds to the shortest distance through the street network obtained from the OSM.

2.2.5. Individual characteristics

Participants' sex was recorded as male and female. Age was calculated at baseline and recoded to form age groups: 18 to 29, 30 to 44, 45 to 64, and 65 to 80 years old. The number of days an individual teleworked per month was recorded as a continuous variable. Car ownership was a binary variable corresponding to whether or not they had access to a car in the household.

2.2.6. COVID-19 pandemic

The first wave was conducted in the pre-pandemic period (2019); 2nd wave corresponded to pandemic time (2021), 3rd wave was when the pandemic-related lockdown was completely lifted (2022), and 4th wave was when people were returning to normal lifestyles (2024). Each survey period had its own distinct characteristics affecting the mode choices. Therefore, dummy variables corresponding to each survey wave were included in the model to understand the mode choices in each scenario.

2.3. Statistical analyses

2.3.1. Analytical sample

We created two datasets in order to test two hypotheses set for this study. 1) The first dataset consisted of participants who had at least participated in two of the four waves, and was used to determine the link between individuals' and built environment characteristics and mode choice. 2) In order to model the possible future travel mode choice at the individual level, we created a separate dataset restricting our samples to only those participating in wave 1 (pre-pandemic; 2019) and wave 4 (post-pandemic; 2023) of our study. This was a wide format dataset where each row represented a person's repeated responses with separate columns consisting of information on mode choice and other relevant variables from 2019 and 2023. Here, the longitudinal component is considered by predicting mode choice in 2023 by factors from 2019 and 2023.

2.3.2. Understanding the mode choice in general

Using the panel data, we modeled transport mode choice with travel, built environment, individual characteristics, and pandemic phases employing multilevel multinominal logistic regression, with a random intercept at the individual level to account for the within-person correlation and between-person heterogeneity in mode choice. The multinominal model is a popular statistical approach used in social science when the outcome is truly a discrete, nominal, and unordered categorical variable, such as mode choice in our study. When the dependent variable is of this sort, the multinomial logit model is more suitable as different people rank the alternative choices differently to maximize their mode of choice (Kwak and Clayton-Matthews, 2002). The generalized multinomial logit model combines several binary logits estimated simultaneously. For example, since the response variable in our study is the choice or non-choice of three transport modes, two binary logits are involved: one for active transport versus private motorized and the other for public transport versus private motorized (Batchelder and Riefer, 1999). This technique has been used by several past studies in modeling discrete mode choice (Rodríguez and Joo, 2004; Ton et al., 2019, 2020). We used an R package, "mclogit" (Elff, 2022), to model the multilevel part and observations were weighted according to the authorities around the globe have set a goal to obtain a modal shift, i.e., encouraging people to use active modes of transport or at least public transport, reducing car dependency (Pan-European Programme, 2014). Therefore, the private motorized vehicle was considered a reference, meaning the odds of choosing active or public transport against private motorized mode were estimated in the model so policymakers could understand the determinants of the mode choice. Covariates that did not improve the model fit (in terms of AIC) were removed from the final model.

2.3.3. Modeling the post-pandemic modal shift

For these analyses, we used the wide-format dataset with respondents repeating in both wave 1 and wave 4. We modeled the mode choices in wave 4 as a function of mode choice in wave 1, with other covariates included in the model. This modeling technique allowed us to understand the tendency of people to use public transit or active transport in the post-pandemic scenario, provided they were commuting with that respective mode in the pre-pandemic period. Simply put, it paints the picture of whether people, in 2023, are shifting back to using the same transport mode as they were in the pre-pandemic period. Covariates, such as gender, tele-workdays, car ownership, duration by car, job accessibility by transit, accessibility to bus and metro station from work, change in teleworking days, and job accessibility by transit from wave 1 to wave 4, a separate dummy variable for people who moved their residential location between the surveys, and RSS variables were selected based on the models' AIC. Job accessibility by transit and duration by car were coded as tertial because the model fit (guided by AIC) improved when these variables were coded that way compared to when a linear association was assumed between these variables and the outcome.

All the models were weighted by survey weights. The weightings for all the valid responses were calculated using the "anesrake" R package (Pasek, 2018). The weights were calculated to match our sample to census tract information of age, income, and gender from the Statistics Canada 2016 Census.

3. Results

The dataset used in investigating the mode choice had 503, 667, 873, and 890 valid participants from the first (2019), second (2021), third (2022) and fourth (2023) waves, respectively. In total, we had a panel of 2933 trips from 1279 participants who participated in any two of the four waves. Likewise, the dataset used for predicting the future mode choice had an analytical sample of 290 participants. Wave-wise descriptive statistics of individuals, trips, built environment, RSS characteristics, and mode choice are presented in Table 1. Fig. 1 illustrates the modal shift between wave 1 and wave 4. Among the original 147 transit users from wave 1, 59.9 % continued using transit services, 21.1 % shifted to active travel and 19.0 % to private motorized vehicles. Among the initial 92 private motorized vehicle users, 15.21 % had switched at Wave 4, 7.6 % to public transit and 7.6 % to an active mode. Regarding active mode travelers (N = 51), 9.8 % shifted to private motorized transport, while 27.5 % towards using public transit in 2023.

3.1. Understanding mode choice

While understanding the coefficients from Table 2, it has to be kept in mind that variables such as age, gender, telework, and car ownership were collected at the personal level. Likewise, variables including duration by car and transit, and distance to the nearest bus and train station were estimated at trip level, while job accessibility and walk score were computed at area level representing the built environment of the neighborhood.

Compared to women, men had 1.50 (95 % CI: 1.09, 2.06) times higher odds of using active transport than private motorized vehicles (Table 2). Participants aged between 30 and 44 were more encouraged to use active transport than participants aged between 18 and 29 (OR: 2.02, 95 %CI: 1.30, 3.14). The propensity of traveling by active and public transit modes were higher (OR: 9.48, 95 % CI: 5.92, 15.20) and (OR: 12.22, 95 %CI: 7.75, 19.25), respectively, among people who do not own a car. One day increase in telework increased the likelihood of using public transit by 1.03 times (95 %CI: 1.01, 1.05). The higher the travel duration by car, the lower the propensity of using active modes for work (OR: 0.96, 95 %CI: 0.93, 0.98, per 5 min), or the higher the likelihood of using public transport (OR: 1.03, 95 %CI: 1.02, 1.04, per 5 min).

Meanwhile, an increase in transit duration to work by 5 min decreased the odds of active and public transport use by 11 % (OR: 0.89, 95 %CI: 0.81, 0.98) and 9 % (OR: 0.91, 95 %CI: 0.85, 0.97), respectively. Participants with a train station within a 500 m radius from their work location have 2.72 times (95 %CI: 1.93, 3.83) and 4.69 times (95 %CI: 3.50, 6.29) higher odds of using active and public transport. Bus stops

Table 1
Descriptive statistics by survey wave. Statistics are numbers (%) or mean (SD) if not specified.

	1 (N = 503)	**Wave 2** (N = 667)	**Wave 3** (N = 873)	**Wave 4** (N = 890)
Individual characteristics				
Gender				
Female	244 (48.5 %)	270 (40.5 %)	424 (48.6 %)	426 (47.9 %)
Age				
18 to 29 years	93 (18.5 %)	114 (17.1 %)	124 (14.2 %)	142 (16.0 %)
30 to 44 years	222 (44.1 %)	287 (43.0 %)	373 (42.7 %)	379 (42.6 %)
45 to 64 years	183 (36.4 %)	255 (38.2 %)	357 (40.9 %)	356 (40.0 %)
65 to 80 years	5 (1.0 %)	11 (1.6 %)	19 (2.2 %)	13 (1.5 %)
Annual income in Canadian dollar				
Less than 60 k	146 (29.0 %)	139 (20.8 %)	169 (19.4 %)	156 (17.5 %)
Between 60–120 k	214 (42.5 %)	276 (41.4 %)	364 (41.7 %)	363 (40.8 %)
More than 120 k	143 (28.4 %)	252 (37.8 %)	340 (38.9 %)	371 (41.7 %)
Marital status				
Married (or common law)	293 (58.3 %)	388 (58.2 %)	510 (58.4 %)	522 (58.7 %)
Tele-workdays per month	1.6 (3.2)	6.0 (7.5)	5.9 (6.8)	6.0 (6.5)
Car ownership (at least one)	359 (71.4 %)	497 (74.5 %)	651 (74.6 %)	671 (75.4 %)
Trip characteristics				
Duration by car (in minutes)	121.7 (102.4)	119.6 (99.6)	120.1 (96.7)	123.6 (101.8)
Duration by transit (in minutes)	39.2 (21.2)	40.7 (23.3)	41.4 (23.2)	43.0 (24.7)
Built environment				
Walk score (0 to 100)				
Very Car dependent (25 to 49)	30 (6.0 %)	85 (12.7 %)	112 (12.8 %)	25 (2.8 %)
Car dependent (25 to 49)	72 (14.3 %)	141 (21.1 %)	132 (15.1 %)	78 (8.8 %)
Somewhat walkable (50 to 69)	78 (15.5 %)	140 (21.0 %)	112 (12.8 %)	136 (15.3 %)
Very walkable (70 to 89)	140 (27.8 %)	233 (34.9 %)	251 (28.8 %)	260 (29.2 %)
Walker's paradise (90 to 100)	183 (36.4 %)	68 (10.2 %)	266 (30.5 %)	391 (43.9 %)
Distance to the nearest train station (work) (<500 m)	203 (40.4 %)	212 (31.8 %)	326 (37.3 %)	330 (37.1 %)
Distance to the nearest bus station (work) (<150 m)	348 (69.2 %)	437 (65.5 %)	585 (67.0 %)	619 (69.6 %)
Residence self-selection (important vs. not important)				
Pleasant for walking (Yes)	409 (81.3 %)	563 (84.4 %)	714 (81.8 %)	708 (79.6 %)
Move around by car (Yes)	229 (45.5 %)	321 (48.1 %)	430 (49.3 %)	430 (48.3 %)
Being near bicycle infrastructure (Yes)	227 (45.1 %)	313 (46.9 %)	352 (40.3 %)	387 (43.5 %)
Being near public transport (Yes)	427 (84.9 %)	494 (74.1 %)	675 (77.3 %)	672 (75.5 %)
Presence of parks and greenspace (Yes)	416 (82.7 %)	564 (84.6 %)	703 (80.5 %)	696 (78.2 %)
Main transport mode				
Private motorized vehicles	155 (30.8 %)	322 (48.3 %)	374 (42.8 %)	352 (39.6 %)
Active transport	94 (18.7 %)	172 (25.8 %)	177 (20.3 %)	214 (24.0 %)
Public transport	254 (50.5 %)	173 (25.9 %)	322 (36.9 %)	324 (36.4 %)

*Active transport includes walking and cycling.

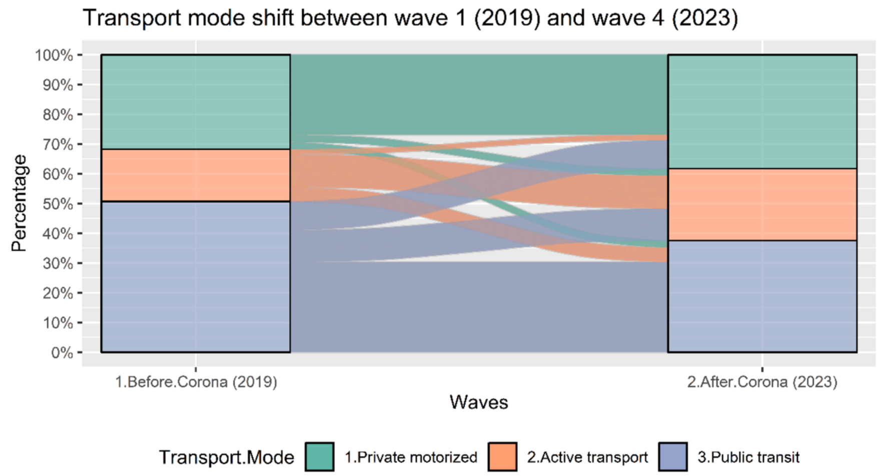

Fig. 1. Mode shift between wave 1 (2019) and wave 4 (2023) for closed number of participants (N = 290).

within a 150 m radius of work increased the odds of public transport use by 64 % (OR: 1.64, 95 %CI: 1.23, 2.18). An increase in the number of jobs accessible from home also increased the likelihood of using both active and public transport. The odds of using active mode increased 1.48 times in 2023 than its use in 2019, however, the confidence interval included the null (95 %CI: 0.90, 2.45). Compared to the pre-pandemic phase (2019), the odds of using public transport during the pandemic (2021) were reduced by 69 % (OR: 0.31, 95 %CI: 0.20, 0.47). Even though the use of public transport gradually increased after the pandemic (2022 and 2023), it never matched the level before the pandemic.

Access to park, bus and train stations from the home location was not adding any information in the model (based on Akaike information criterion (AIC)), thus was not retained in the final analyses. Bike Score® (Winters et al., 2016), an index measuring whether a neighbourhood is good for biking on a scale from 0 to 100, had a multicollinearity issue with the walk score (variance inflation factor greater than 5), so we removed it from the model. We tested the interaction between COVID-19 phases and built environment and individual characteristics, but none were significant, so they were not retained in the model.

3.2. Post-pandemic modal shift

When it comes to understanding the modal shift among those people who were using active and public modes in the pre-pandemic period, a great number of active mode users shifted back to using the same mode in the post-pandemic phase (OR: 52.71, 95 %CI: 8.68, 320.20) (Table 3). Meanwhile, a large portion of active mode users in 2019 switched to being public transport users in 2023 (OR: 32.11, 95 %CI: 6.23, 165.44). The odds of pre-pandemic public transport users sticking to the same modes in the post-pandemic scenario were 22.54 times higher than choosing private motorized vehicles (95 %CI: 7.29, 69.66). The propensity of public mode users in wave 1 switching to active mode in wave 4 was comparatively lower but still statistically significant (OR: 7.27, 95 %CI: 1.91, 27.67). Individual level variables, namely, sex and telework, and trip-related variables, such as distance to the nearest bus station and train station and duration by car, were not associated with mode choice in the post-pandemic scenarios. Job accessibility by transit, an area-level variable, was a significant predictor of active transport mode, where an increase in job accessibility was linked to greater odds of using active mode compared to private motorized vehicles (Table 3).

4. Discussion

The first part of our analysis associated individual, trip, and built environment characteristics with transport mode choice. It also revealed that public transport, which significantly decreased during the pandemic, gradually increased in the two post-phases of the pandemic, even though it did not reach the level it had before. These findings led us to the second analysis, where we explored the tendencies to sticking and shifting among three modes (active mode, public transit, and private motorized-vehicle), limiting our sample to only those 290 participants who responded to survey waves in pre (2019) and post-pandemic (2023) periods. Our study reports that the odds of public transit users sticking to the same mode in the post-pandemic scenario are higher than them shifting towards private car use, while the rebound of active travelers was even stronger.

Supporting the findings from our study, several other studies also have reported the willingness of people to use public transit in the post-pandemic phase (Monterde-i-Bort et al., 2022). (Harrington and Hadjiconstantinou, 2022; Monterde-i-Bort et al., 2022; Palm et al., 2022; Przybylowski et al., 2021; Thomas et al., 2021). However, unlike our study recording the trip level data, most of these studies were conducted during the COVID-19 lockdown, asking participants about the transport mode they would prefer once the lockdown was fully lifted. Another consistency found across previous studies and ours is that active transport users are switching back to using the same mode after the pandemic, with even some car users being interested in switching to active mode as their main transport mode (Monterde-i-Bort et al., 2022; Nikiforiadis et al., 2020).

In order to speed up the rate of shifting back to public transit, authorities should evaluate the effects of psychological factors hindering the transit choice and take action to overcome them (Abu-Rayash and Dincer, 2020; Passavanti et al., 2021). Meanwhile, making some improvements in public transport mode would prevent losing those who really intend to stick with or want to shift to public transport for work trips after the pandemic (Eisenmann et al., 2021). Improving little things that are known to all of us, such as increasing the frequency of transit to the level it was before, reducing the crowds at stops, introducing cashless and contactless payment mechanisms, alternate sitting arrangements to maintain social distancing, real-time information on transit availability, regular disinfection of the vehicles, ensuring other hygiene measures (Gkiotsalitis and Cats, 2021) would encourage people in again using public transit. A survey asked commuters about their possibility of using public transit if these measures were applied, and 25.6 % of the passengers said yes, while 53.6 % replied probably yes (Das et al., 2021). In a general scenario, as in our study, working on other strategies, namely establishing transit stops in proximity (Ababio-Donkor et al., 2020; Buehler, 2011; Ewing and Cervero, 2010), reduction in fare (Ha et al., 2020), minimizing travel duration (Dėdelė et al., 2020; Ha et al.,

Table 2
Associations of individual, trip and built environment characteristics with the likelihood of choosing active or public transport compared to private-motorized transport; estimated from a multilevel multinominal model with a random intercept at the individual level. (All waves repeating observations, participants: 1279, trips: 2933).

Variables	Active transport+	Public transit
Personal characteristics		
Males ((ref: females)	1.50 (1.09, 2.06) *	0.81 (0.61, 1.06)
Age (ref: 18 to 30)		
Between 30 and 44	2.02 (1.30, 3.14) **	1.19 (0.81, 1.75)
Between 45 and 64	1.46 (0.92, 2.32)	0.93 (0.63, 1.39)
Between 65 and 80	0.23 (0.05, 1.09)	0.56 (0.16, 1.93)
Car ownership (ref: yes at least one)	9.48 (5.92, 15.20) **	12.22 (7.75, 19.25) **
Tele-work per month (continuous)	1.02 (0.99, 1.05)	1.03 (1.01, 1.05) **
Trip Characteristics		
Duration by car (per 5 min)	0.96 (0.93, 0.98) **	1.03 (1.02, 1.04) **
Duration by transit (per 5 min)	0.89 (0.81, 0.98) *	0.91 (0.85, 0.97) **
Measures of built environment		
Walk score (home) (ref: 0 to 24 (very car dependent)		
Car dependent (25 to 49)	0.59 (0.23, 1.47)	1.07 (0.61, 1.89)
Somewhat walkable (50 to 69)	0.74 (0.30, 1.79)	1.19 (0.67, 2.12)
Very walkable (70 to 89)	0.76 (0.31, 1.89)	1.28 (0.69, 2.38)
Walker's paradise (90 to 100)	0.66 (0.24, 1.85)	0.91 (0.43, 1.92)
Distance to the nearest train station (work) (Ref: >500 m)	2.72 (1.93, 3.83) **	4.69 (3.50, 6.29) **
Distance to the nearest bus station (work) (Ref: >150 m)	1.39 (0.99, 1.94)	1.64 (1.23, 2.18) **
Job accessibility by 45 min transit (per 100000)	1.18 (1.06, 1.31) **	1.12 (1.02, 1.22) *
Residence self-selection (important vs. not important)		
Pleasant for walking	0.96 (0.61, 1.51)	1.11 (0.77, 1.60)
Move around by car	0.29 (0.21, 0.41) **	0.35 (0.26, 0.47) **
Being near bicycle infrastructure	2.44 (1.74, 3.44) **	1.12 (0.83, 1.49)
Being near public transport	1.53 (0.99, 2.36)	5.88 (3.96, 8.73) **
Presence of parks and greenspace	0.71 (0.45, 1.11)	0.67 (0.46, 0.98) *
CoVID-19 (ref: Before)		
During	1.01 (0.61, 1.66)	0.31 (0.20, 0.47) **
After	0.97 (0.59, 1.58)	0.50 (0.34, 0.74) **
Late after	1.48 (0.90, 2.45)	0.63 (0.42, 0.94) *

+Active transport includes walking and cycling.
Level of significance (p-value): ** <0.01 and * <0.05.

Table 3
Mode choice in wave 4 based on mode choice in wave 1 among 290 participants (taking private motorized vehicle as a reference).

	Active transport* (wave 4)	Public transit (wave 4)
Active transport* (wave 1)	52.71 (8.68, 320.20)	32.11 (6.23, 165.44)
Public transit (wave 1)	7.27 (1.91, 27.67)	22.54 (7.29, 69.66)
Males (ref: females)	1.07 (0.37, 3.10)	0.59 (0.24, 1.44)
Tele work	0.99 (0.82, 1.21)	1.01 (0.86, 1.19)
Tele work change (wave4 −wave1)	1.00 (0.93, 1.08)	0.99 (0.93, 1.05)
Job accessibility by transit (Ref: 1st tertile)		
2nd tertile	20.89 (2.13, 204.91)	1.63 (0.53, 4.96)
3rd tertile	25.40 (2.63, 244.88)	2.21 (0.62, 7.90)
Job accessibility change (w4-w1)	0.99 (0.72, 1.35)	1.00 (0.77, 1.31)
Duration by car (Ref: 1st tertial)		
2nd tertile	1.15 (0.33, 3.97)	1.81 (0.54, 6.03)
3rd tertile	0.10 (0.02, 0.63)	2.03 (0.59, 6.96)
Distance to the nearest bus station (work) (ref: >150 m)	2.55 (0.76, 8.60)	1.66 (0.64, 4.32)
Distance to the nearest train station (work) (ref: >500 m)	0.66 (0.23, 1.93)	1.99 (0.79, 4.99)
Residential self-selection (important vs. not important)		
Move around by car	0.10 (0.03, 0.32)	0.22 (0.08, 0.57)
Being near public transport	3.03 (0.65, 14.12)	4.43 (1.17, 16.74)
Moved (yes vs. no)	1.08 (0.34, 3.40)	0.94 (0.33, 2.72)

*Active transport includes walking and cycling.

2020), well-connected transit network (Asadi Bagloee et al., 2011) and comfortability of the ride (Wu et al., 2023) might attract even new commuters towards public transport. In the local context, the completion of the Exo Deux-Montagnes line and the new light-rail network might help increase transit ridership in the near future. It should also be noted that the adaptation of teleworking modality in various job industries, even after the pandemic is over, might be a reason why the use of public transit hasn't risen to pre-pandemic levels.

As for the second scenario, apart from reliable active travelers, there are public transport passengers directed towards active modes during the pandemic and years after the pandemic. Even though the decrease in transit ridership is undesirable, increasing active mode use will contribute to a sustainable urban environment while helping people gain daily recommended physical activity (Bista et al., 2020). Due to this reason, transport authorities should pay a great deal of attention to this scenario. Or else, failing to meet their satisfaction may divert these commuters towards using private cars or cab services (Das et al., 2021). Provisional measures, such as the concept of pop-up bike lanes during COVID-19, were a good policy and must be maintained and expanded beyond the pandemic to make the city cycle-friendly (Nikitas et al., 2021). For example, Montreal installed 88 km of new cycle lanes in 2020, of which 29 km were temporary COVID lanes, in order to compensate for the reduction in transit services (Buehler and Pucher, 2021). Examination of existing pedestrian and bicycle conditions regarding route connectivity, the necessary width of the lanes, and separating it from motorized vehicles might help build a sustainable bicycle network (Nikiforiadis et al., 2021). In normal conditions, well-constructed sidewalks (Rodríguez and Joo, 2004; Saelens et al., 2003) and promoting greenery (Jia and Fu, 2014; Krenichyn, 2006; McCormack and Shiell, 2011) also encouraged people to adopt active transport. Strengthening the integration of public and active modes would be a breakthrough in promoting sustainable transport modes (active or public transport), which a lot of cities have already started. For example, installing bike-share parking right outside the transit station makes it more convenient for people to travel from and to the station.

However, a seemingly challenging scenario is when public transit and active mode users switched to private car use during COVID-19 and stuck to that mode even a few years past the pandemic (Palm et al., 2022). This problem is expected to worsen with the huge number of people buying cars in the coming days. For example, 9 % Canadians intended to purchase a car in 2021, and the statistics were expected to go up to 44 % by the end of 2024 (Palm et al., 2022). As suggested in our study, the likelihood of using a car is way higher among people owning a car than those who do not (Paulley et al., 2006; Swait and Ben-Akiva, 1987; Vij et al., 2017). If so, we can expect to see a higher share of people using cars in the coming days and, consequently, higher emissions of greenhouse gases than before the pandemic and let alone its impact on country's economy. Employer sponsoring monthly transit passes to employees might discourage private car use among workers, since people owning a transit pass are more likely to use the service than people who do not (Badoe and Yendeti, 2007). Evidently, car owners are also aware of the environmental and personal benefits of active and public transport and have a silent desire to change, and they just need a little push or encouragement. With the prevailing fear of COVID-19 infection, studies have highlighted the importance of psychological aspects and glaring beyond the physical infrastructure and built environment when motivating car users to change their mode choice (Harrington and Hadjiconstantinou, 2022).

4.1. Limitations

Findings from our study might not be generalized to the overall trips made by people in daily life, as we only analyzed work-related trips. Logically, work-related trips are usually longer than general daily trips, such as grocery or family chores, and may demand a transport ridership. The confidence interval associated with the odds ratios presenting the likelihood of mode shift (Table 3) was very wide due to a lack of statistical power ($N = 290$). Furthermore, because of the smaller sample size, we could not stratify our modal shift analyses in terms of socio-economic attributes and understand which subpopulations prefer to travel using certain travel modes. Thus, a study with a larger sample size would provide more certainty on our study's results and help understand travel behavior across different socio-economic groups.

4.2. Conclusion

Our study in Montreal showed that work-related travel done by public transit dropped significantly during COVID-19, while private motorized vehicle use increased. Since active travel was found to be more resilient to this sort of crisis, investments to make active transport feasible for everyone might be a strategy towards sustainable transport. Similarly, shifting back to public transit might be partially linked to the quality of the transit infrastructure, therefore, transport authorities might need to pay attention to making transit service more efficient and safer in order to promote the desired shift.

CRediT authorship contribution statement

Sanjeev Bista: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benoit Thierry:** Software, Resources, Methodology, Data curation. **Rodrigo Victoriano-Habit:** Resources, Methodology, Investigation. **Ahmed El-Geneidy:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **Yan Kestens:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Data availability

Data will be made available on request.

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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