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Exploring the changes in the interrelation between public transit mode share and accessibility across income groups in major Canadian cities in the post-pandemic era

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ABSTRACT

The COVID-19 pandemic has impacted the travel behaviour of urban residents in an unprecedented manner, especially public transit (PT) users. PT has experienced a decline in ridership around the world early in the pandemic and has been struggling to rebound again to the pre-pandemic levels, whereas other modes have reached their pre-pandemic levels. PT agencies have been trying to attract users back through service improvements and other policies; nevertheless, the impacts of policies that were effective prior to the pandemic are not guaranteed in the post-pandemic world due to the lasting effects of the pandemic on travel behaviour. This study compares the changes in the impacts of accessibility, the ease of reaching destinations, to jobs by PT on commute mode share pre- and post-pandemic (2016 and 2021) with an equity lens in the three largest metropolitan regions in Canada: Toronto, Montreal, and Vancouver. Results show that planning for accessibility is still an impactful tool to increase PT mode share in the post-pandemic era, yet the magnitude of the impact has declined by almost 50% in Toronto and Montreal and 30% in Vancouver for low-income groups. In the post-pandemic era, the impact of accessibility on PT mode share remains higher for the low-income compared to other-income groups, which is similar to the pre-pandemic times. Understanding the changing effects of accessibility, a major land use and transport planning tool, on travel behaviour is important as PT agencies are developing strategies to restore pre-pandemic levels of ridership and increase it to reach their sustainability goals.

1. Introduction

The mitigating strategies imposed by the outbreak of COVID-19 had remarkable impacts on travel behaviour (Javadinasr et al., 2022; Kapatsila et al., 2023a; Kolarova et al., 2021; Paul et al., 2022; Shamshiripour et al., 2020) and profoundly influenced public transit (PT) ridership negatively worldwide (Das et al., 2021; Tirachini and Cats, 2020). In Canada, PT ridership levels decreased between 2016 and 2021 by 59% in Toronto, % 46% in Montreal, and 42% in Vancouver (Statistics Canada, 2017, 2023a). As travel and social-distancing restrictions came to an end, the world gradually returned to some of its pre-pandemic state. Nonetheless, this transition was accompanied by shifts in some travel habits and preferences. For example, many employees currently prefer working from home or a hybrid workstyle (Mohammadi et al., 2023) and many institutions have been responding to that through adopting hybrid work policies (City of Toronto, 2023; Public Safety Canada, 2023). Post-pandemic studies reported an increase in the use of private vehicles and a decrease in PT use especially among commuters to work (Abdullah et al., 2021; Javadinasr et al., 2022; Kolarova et al., 2021). These changes challenge many of the known facts when it comes to travel behaviour, such as the magnitude and impact of the built environment on mode choice.

Accessibility, the ease of reaching destinations (Hansen, 1959), has been established as a reliable measure of the built environment, as it incorporates the land use and transport systems in one measure. Previous research has established the impact of accessibility on travel behaviour (Cui et al., 2020; Legrain et al., 2015), especially PT mode choice. The pandemic had a clear impact on travel behaviour which has been shown to influence travel attitude (Kroesen et al., 2017; Rahman and Sciara, 2022). Based on the idea of changing travel behaviours and attitudes, we can assume that the factors impacting PT mode choice could have witnessed significant changes post-pandemic. To our

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knowledge, the changes in the effects of accessibility on PT mode share have not yet been studied. Our study aims to understand the variations in the impact of accessibility on PT mode share in the post-pandemic era and compare it to the pre-pandemic times from an equity perspective. We investigate these impacts for low and other-income groups in the three largest metropolitan regions in Canada: Toronto, Montreal, and Vancouver. As many PT agencies around the world are struggling with the decline in ridership, an understanding of the changing effects of accessibility, a major planning tool, on travel behaviour will help inform their decisions on services additions or cuts to achieve their sustainability goals.

2. Literature review

Transport is a cornerstone of sustainable development (UN High-level Advisory Group on Sustainable Transport, 2016). In their transport plans, many cities aspire to achieve higher sustainable mode share. For example, the City of Vancouver's 2040 plan, which was developed in 2016, aims for two-thirds of all trips to be made by foot, bike, or transit (City of Vancouver, 2012). Most of the transport plans' mode share targets, however, were set before the COVID-19 pandemic, which deeply impacted transit ridership and perception. Most North American agencies reduced service levels in the pandemic's early months when COVID-19 restrictions were highest (DeWeese et al., 2020). By mid-2021, many had returned to pre-pandemic service levels in the hopes of bringing ridership back (González-Hermoso and Freemark, 2021). However, today many agencies started to understand that the impacts of service provisions are no longer the same as they were in pre-pandemic times. Many agencies are exploring several options for service cuts and changes to address their financial deficit (Levitz, 2023), yet to what extent these changes will impact ridership is still unknown.

As much as COVID-19 had an impact on the decisions of transit agencies, it also had a major influence on travelers' behaviours and attitudes. A longitudinal study in Toronto and Vancouver by Palm et al. (2022) found that post-pandemic, public transit has seen a decline in choice riders, the ones who have access to multiple transport options and deliberately opt to use public transit for specific trips (Guerra, 2022). They also revealed a surge in car ownership among previous transit riders who found that having a car is necessary and helpful during the pandemic. In another study, Palm et al. (2023) revealed that people who depended on transit before the pandemic tended to keep using it for essential needs such as grocery shopping, while those who used transit less replaced these trips by online grocery delivery. Shopping trips were not the only ones impacted by COVID-19. Javadinasr et al. (2022) and Anik and Habib (2023) display the potential replacement of work trips by telecommuting even in the post-pandemic era. Building on the research investigating travel behaviour changes after the pandemic, our study aims to examine the shifts, if any, in the impacts of the built environment on mode shares before and after the pandemic in various regions across Canada.

One major built environment factor that has been found to impact transit use is accessibility by public transit. Accessibility is considered one of the most comprehensive measures that link land use and transport systems to assess how they benefit the population in reaching opportunities (El-Geneidy and Levinson, 2022; Geurs and Van Wee, 2004; Handy, 2020). It is often used as a tool to explain the equity impacts of land use and transport policies and projects (Allen et al., 2021; Deboosere and El-Geneidy, 2018; Ermagun and Tilahun, 2020; Geurs et al., 2016; Martens, 2012). Understanding the impacts of service changes through accessibility on mode choice is essential as many agencies include them in their planning goals as effectiveness measures (Boisjoly and El-Geneidy, 2017). The relationship between accessibility by PT and its use has been well established as a positively correlated one (Moniruzzaman and Páez, 2012; Owen and Levinson, 2015). People who tend to use public transit more are the ones experiencing higher levels of accessibility by public transit. A recent study by Cui et al. (2020) confirmed the impact of accessibility on mode share for low- and other-income groups in eleven Canadian cities through a series of linear regressions using 2016 census data. They found that accessibility is a predictor of PT mode share and that the positive impact of increasing accessibility is much higher for the low-income groups' mode share. We hypothesise that this impact of accessibility on PT mode share has changed after the pandemic due to the service cuts, changes in job distributions, and telecommuting rates, which could have a major impact on travel behaviours and attitudes.

When it comes to measures of accessibility, cumulative opportunities measure is one of the most commonly used, due to its ease of interpretation, and communication to the public and policymakers (El-Geneidy and Levinson, 2022). In this measure of accessibility, all the opportunities (destinations) available within a predefined travel time threshold are weighted equally (Geurs and van Eck, 2001). Several other methods are used to measure place-based accessibility including gravity-based accessibility which weighs opportunities based on the travel time necessary to reach them. This method allows for the inclusion of opportunities that could be discarded in the cumulative measures if they are not within the set time threshold. While this measure improves the approximation to reality, it also requires an extensive amount of additional data and is more challenging to compute, interpret, and communicate to the policymakers and the public. Comparison between cumulative opportunities and gravity-based measures found high correlation between the two measures in the North American context (El-Geneidy and Levinson, 2006; Giannotti et al., 2021; Kapatsila et al., 2023b; Palacios and El-Geneidy, 2022). This suggests that using cumulative opportunities is sufficient to present the built environment adequately when examining a variable such as public transit mode share and allow for the ease of communication of the results. Our research seeks to build upon prior studies concerning accessibility and mode choice by investigating the effect of its recent effects on PT mode share in the post-pandemic era and compares that to the pre-pandemic time while focusing on the aspect of equity of these impacts.

3. Data

3.1. Census data

The main data sources for this study are the 2016 and 2021 Canadian population census and commuting flows (CCF) (Statistics Canada, 2017, 2023a). The CCF tables provide the number of workers commuting between their home and work census tracts (CTs) by income groups and mode of transport. These tables were used to define the threshold for the low and other-income workers in each region and year. Low-income workers were defined as the lowest paid 30% in each region following Deboosere and El-Geneidy (2018). As the census income groups are defined in 5 k to 20 k CAD increments, the threshold was set as close as possible to the 30th percentile. This resulted in 30 k CAD being the low-income cut-off threshold for Toronto, Montreal, and Vancouver in 2016, and 40 k CAD being the threshold in 2021 for the three regions. The same thresholds were used to calculate the number of low and other-income jobs in each region's CTs, which were used to calculate accessibility to jobs. For the other-income workers and jobs, we used the income groups above the set threshold for 2016 and 2021. In other words, the other-income workers are defined as the ones who earned >30 k in 2016 and >40 k in 2021. This logic was applied to all three Census Metropolitan Areas (CMAs).

Public-transit mode shares were calculated from the CCF as the share of low- and other-income commuters living in each CT who use public transit to commute. Low-income workers commuting via transit were divided by the total number of low-income commuters, and a similar calculation was performed for other-income commuters. A limitation faced in this part was data suppression which is the deletion/zeroing of certain values, such as the number of commuters within an income bracket. This is applied when the values are below a certain threshold set by the data provider (Statistics Canada, 2016). In some instances, data suppression within CCF income brackets caused discrepancies between the sum of the income groups' number of trips and the total number of trips reported per CT. In cases where both low and other-income number of trips equalled zero, due to the suppression of data within income brackets, and the total commuters provided by the CFF was non-zero, the CT was excluded from the dataset. If the two income groups did not add up to the total and one group had a non-zero value, the missing portion was assumed to be represented by the other group to complete the total. CTs with a transit mode share higher than 80% for any income group were excluded from the analysis as they were found to be the result of census data suppression, resulting in mode-share overestimation.

Although Statistics Canada offers data at a more detailed spatial resolution known as Dissemination Area (DA) level, the information at this level is subject to even stricter data suppression compared to the Census Tract (CT) level. This heightened suppression is a result of the smaller population residing in and commuting from these DAs, leading to numerous values being suppressed to safeguard the privacy of individual population members. Despite the theoretical potential for more accurate insights through analysis at the DA level, the prevalence of missing data poses a significant risk of distortion. Consequently, we have chosen to utilize the higher-level CT data for our analysis to mitigate the impact of data suppression.

3.2. Spatial data

The regional accessibility by PT to jobs was calculated using the number of jobs per CT (commuters arriving in the CT), General Transit Feed Specification (GTFS) data, and OpenStreetMap networks. GTFS data was obtained from Transitland using an API for October 2016 and June 2021, as these dates guaranteed the availability of the schedules for all transit systems in the three regions. The OpenStreetMap street network was obtained for each region through BBBike extracts. We used the r5r package in R with GTFS data and the OSM network for each region as inputs to calculate a travel time matrix (TTM) between CT centroids (Pereira et al., 2021). This TTM presents the shortest travel time by public transit between each origin and destination (CTs) for a regular Wednesday traveling between 8 AM and 9 am then averaged to account for schedule variability. The calculated travel times include access, egress, waiting, in-vehicle, and transfer times if applicable.

Cumulative opportunities measures were calculated for the three studied regions. The travel-time threshold was set to 45 min as it is closest to the median travel times by public transit for the three metropolitan areas (Statistics Canada, 2017, 2023b) in both time periods, as suggested by Kapatsila et al. (2023b). Accessibility to low- and other-income jobs was calculated separately by adding the number of these jobs accessible from each CT centroid within 45 min of travel by PT. To allow for comparisons between different income groups, regions, and time periods, we divided the resulting accessibility values per CT by the total number of jobs available in each CMA, resulting in a proportional accessibility measure. This represents the percentage of low and other-income jobs in the CMA accessible from each CT.

As an indicator of the availability of high-quality PT service in a CT, we calculated the shortest distances on the road network between CT centroids and the closest rapid transit station using the dodgr package in R (Padgham, 2023) for each region. Rapid transit comprises metro, commuter trains, and bus rapid transit (BRT). We retrieved the coordinates of the stations from Transitland based on the data provided by the regions' respective agencies. The same method was applied to calculate the closest highway ramp for each CT centroid.

4. Methods

The study aims to understand the relationship between public transit mode share and accessibility to jobs by PT for different income groups and how it has changed throughout the pandemic for three different Canadian regions. We analyze the mode share of low-income workers to low-income jobs and the same for other-income workers and jobs. We first conduct an exploratory analysis through scatterplots to represent the relationship between accessibility and PT mode share by income group for all regions. We then investigate this relationship by estimating multiple linear regression models with PT mode share in each CT as the dependent variable. For each CMA, we estimate four models to inspect the differences between 2016 and 2021 for the low- and other-income groups. The dependent variable in each model represents the share of PT users within an income group relative to the total number of workers in that income group (e.g., low-income transit users/ total low-income workers) commuting to work. PT accessibility to jobs divided by the total number of jobs in the region is our key independent variable and, in each model, it corresponds to the income group that is being modeled. Based on the exploratory analysis, a squared term of this accessibility percentage is included as an independent variable to capture the non-linear relationship between accessibility and PT mode share that was revealed in the scatter plots (Cui et al., 2020).

We incorporated other socio-demographic variables, such as average age and household size into our models enabling the consideration of the CTs population characteristics. Additionally, we take into account the effects of COVID-19 on travel behaviour and telecommuting by including the percentage of employees working from home as an independent variable (Javadinasr et al., 2022). Other built-environment characteristics were included in the models as controls, such as population density and the distance to the closest rapid transit station (Ewing and Cervero, 2001). The distance to the closest highway ramps were tested and was revealed to be statistically insignificant; therefore, it was excluded from the models.

5. Results and discussion

5.1. Context maps

The bivariate maps in Fig. 1 display the changes in accessibility to jobs by public transit between 2016 and 2021 for the three studied regions. The maps display the distribution of proportional accessibility to low- and other-income jobs in relation to each other. Proportional accessibility is the number of accessible jobs (low or other-income ones) divided by the total numbers of jobs in the CMA. It is important to emphasize that although certain areas have high accessibility for both low- and other-income jobs in 2016 and 2021, that does not imply that the number of accessible jobs remained similar between the two years as the map display relative values (high and low accessible jobs). Overall, in the central areas characterized by significant intersection of rapid transit networks, accessibility is highest for both low- and other-income jobs in the two time periods.

Moving outwards of city centers, the distribution of accessible jobs for both groups exhibits some changes in all three CMAs. These changes are attributed to variation in the types of jobs available (low- or other-income jobs) and changes in infrastructure. The changes in infrastructure include the addition of new transit lines such as the Line 1 Yonge–University western extension that opened in late 2017 (Toronto Transit Commission, 2023) and the Millennium Line Evergreen Extension in Vancouver that started operating in late 2016 (Infrastructure BC, 2023). On the opposite side, in Montreal, the transit network was impacted by some closures and rerouting due to the construction of the new light-rail network, including the complete closure of the Exo Deux-Montagnes line by the end of 2020 (Gouvernement du Québec, 2023).

To illustrate an example for the changes in accessibility to different types of jobs, in the Eastern side of Toronto; there was a higher accessibility for low-income jobs compared to other-income ones in 2016. However, for many CTs, this ratio changed in 2021 and proportional accessibility became intermediate for both jobs' groups. These changes are seen in the three regions in different ways as higher or lower

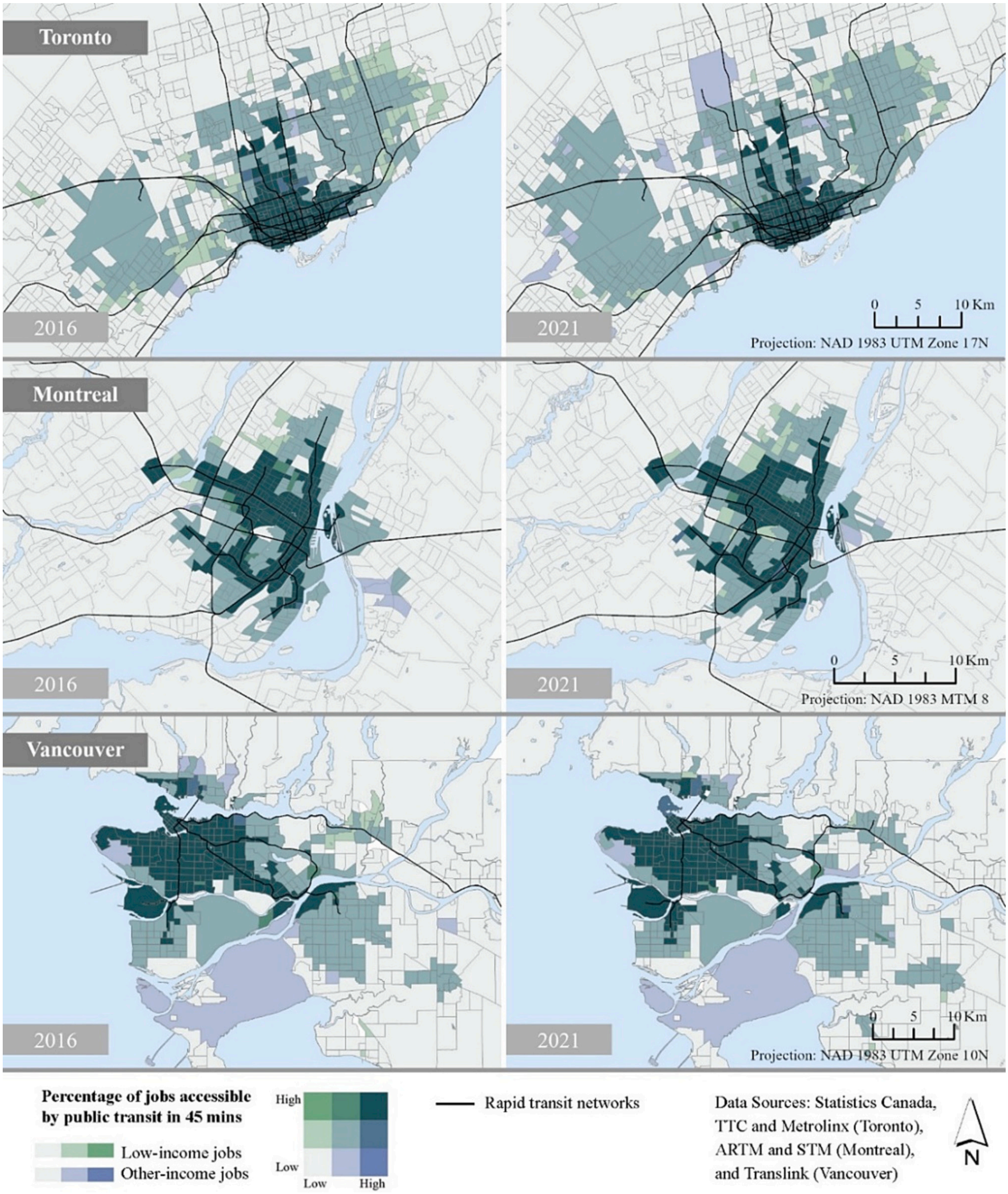

Fig. 1. Proportional accessibility to low- and other-income jobs by public transit in 45 min for Toronto, Montreal, and Vancouver in 2016 and 2021.

accessibility to low-income jobs, or other-income ones in relation to each other. To account for these dynamic changes in accessibility to low- and other- income jobs, we estimate our regression models for each income group individually.

5.2. Descriptive statistics

Table 1 includes descriptive statistics of the data used in the models by year and region. It is observed that the mean PT mode share is always higher for low-income groups compared to other-income ones across all regions and in the two time periods. Comparing between years, we find that the mean PT mode share decreased in 2021 for both income groups in all CMAs, with a contrasting increase in the mean car mode share. This could mainly be attributed to the COVID-19 social distancing interventions executed by transit agencies that significantly reduced the levels of PT ridership (Kamga and Eickemeyer, 2021; Palm et al., 2021)

Table 1
Descriptive Statistics for the CTs in the three studied CMAs.

	Toronto				Montreal				Vancouver			
	2016		2021		2016		2021		2016		2021	
Region Population	5,928,040		6,202,225		4,104,074		4,291,732		2,463,431		2,642,825	
Number of CTs	$N = 1139$		$N = 982$		$N = 944$		$N = 817$		$N = 463$		$N = 465$	
Income Level	Low	Other	Low	Other	Low	Other	Low	Other	Low	Other	Low	Other
PT Mode Share (%) *	32.14 (17.54)	23.68 (13.66)	21.62 (13.95)	13.1 (10.42)	31.43 (18.48)	23.31 (14.06)	23.94 (15.36)	14.36 (11.48)	28.75 (13.87)	16.87 (10.14)	21.44 (12.48)	9.8 (7.12)
Car Mode Share (%) *	55.8 (22.19)	70.24 (19.44)	60.76 (23.07)	73.01 (18.68)	53.83 (24.64)	67.84 (21.44)	54.49 (25.35)	68.05 (24.06)	56.98 (19.08)	74.35 (17.03)	59.38 (19.21)	76.32 (16)
Accessibility by PT in 45 mins (%) *	1.52 (1.9)	4.16 (6.17)	1.7 (1.72)	3.59 (4.26)	3.32 (3.87)	8.85 (10.49)	3.86 (4.13)	7.17 (7.79)	3.66 (3.88)	8.59 (9.72)	4.5 (4.15)	8.37 (8.16)
Total Jobs (10,000) *	0.24 (0.71)		0.13 (0.33)		0.19 (0.49)		0.14 (0.26)		0.23 (0.46)		0.15 (0.23)	
Employed Population (%) *	60.81 (7.09)		55.29 (6.94)		61.07 (8.23)		60.56 (7.15)		61.28 (7.56)		59.66 (7.22)	
WFH Employees (%) *	7.42 (3.96)		33.69 (12.9)		6.9 (3.1)		27.57 (11.24)		8.56 (4.4)		25.93 (10.01)	
Age *	40.27 (3.95)		40.98 (3.72)		40.65 (4.25)		41.02 (3.98)		41.38 (4.01)		41.85 (3.9)	
Household structure *	2.84 (0.6)		2.82 (0.62)		2.31 (0.41)		2.28 (0.39)		2.65 (0.56)		2.62 (0.57)	
Median Income *	8.56 (3.08)		10.09 (2.98)		6.6 (2.67)		7.69 (2.52)		7.84 (2.16)		9.43 (2.2)	
Population density (1000/km2) *	5.59 (6.44)		6.66 (7.88)		5.67 (5.19)		6.44 (5.54)		4.69 (4.95)		5.55 (5.66)	
Distance to Station (km) *	3.7 (4.98)		3.64 (5.09)		4.59 (6.03)		4.3 (5.54)		6.05 (6.07)		5.15 (5.06)	

* Mean (SD)

and the working-from-home policies.

In 2021, the mean percentage of accessible jobs for low-income groups slightly increased compared to 2016, while it decreased for other-income groups. The increase in the low-income accessibility percentage can be attributed to two things: the decrease in the total number of jobs, and the increase in telecommuting which is considered a more plausible option for other-income jobs than low-income ones (Anik and Habib, 2023). Therefore, the increase in accessibility percentages between the two years does not mean that accessibility to jobs was enhanced for the lower-income group as the decrease in the number of jobs was disproportionate for low- and other-income jobs that people commute to in 2021. As census population data is not disaggregated by income groups, other variables are presented for the CT as a whole. The increase in the percentage of employees working from home (WFH) is noteworthy, as WFH employees in 2021 account for more than a quarter of the population in each CMA. Average age and household size remain similar in 2021 compared to 2016 for each CMA.

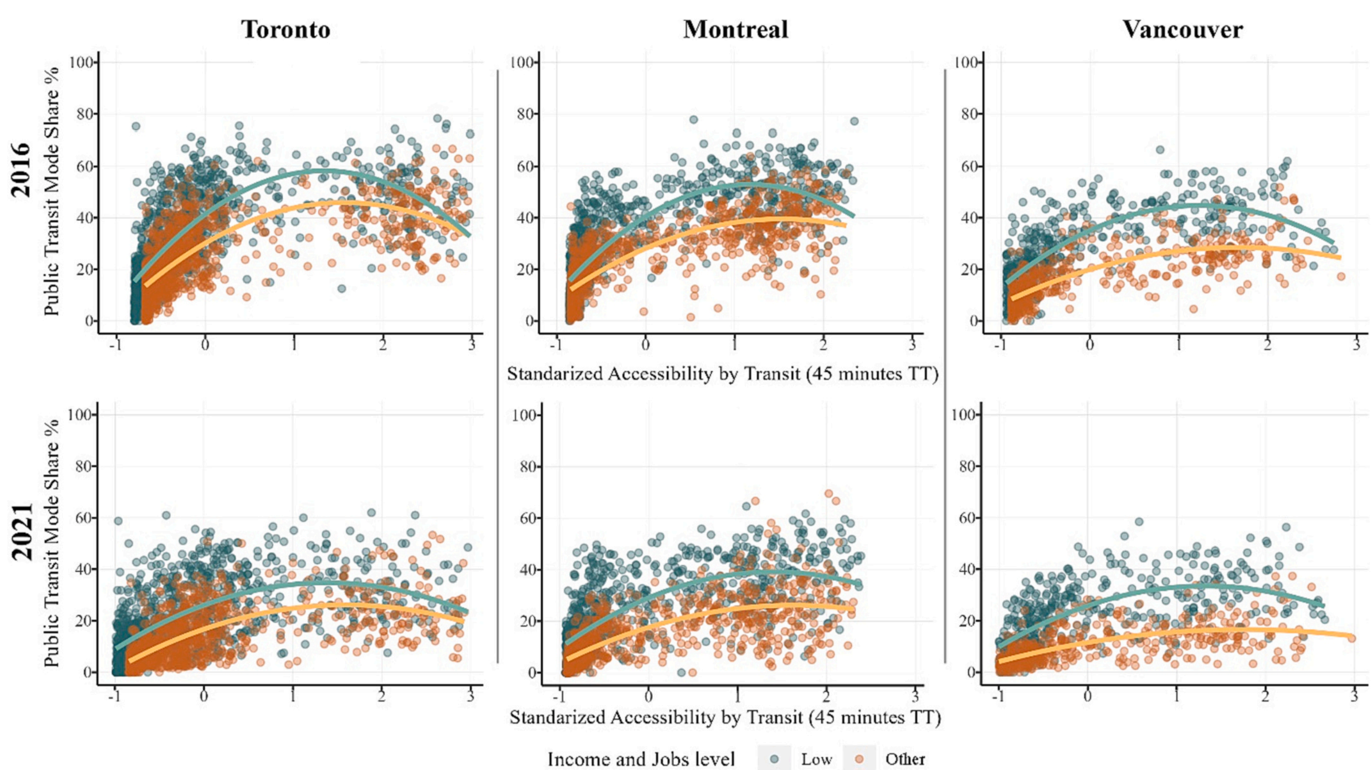

Fig. 2. Scatter plots for PT mode share and standardized accessibility for low and other-income groups in Toronto, Montreal, and Vancouver in 2016 and 2021.

5.3. Public transit mode share and accessibility

To investigate the relationship between PT mode share and accessibility for both income groups, Fig. 2 presents scatter plots of these two variables per region, income group, and year. To allow for comparison between the income groups, we use normalized accessibility (z-scores). We fitted a polynomial model as the best-fit curve, as it was found to be the most accurate in previous research (Cui and El-Geneidy, 2019). The plots reveal a non-linear relationship that applies to both income groups, where the mode share increases with the improvement of accessibility until a certain point and then starts to decrease for higher accessibility. These results are consistent with those presented by Cui and El-Geneidy (2019) for 2016.

In both years and across the regions, we find low-income groups use public transit more than other-income ones at any accessibility level. In 2016, when accessibility improved significantly (within z-scores of −1 and 1), there was a surge in PT usage, particularly in Montreal and Toronto. For all regions in 2021, we find that PT mode share is much lower than in 2016 at all accessibility levels. Factors influencing such change could be the increasing rates of WFH, the decrease in the number of on-site jobs and the decreased activity around denser city centers. There was a notable decline in PT usage at very high levels of accessibility in 2016 which is not as evident in 2021.

5.4. Statistical model and discussion

Regression results for the three CMAs, Toronto, Montreal, and Vancouver, are presented in Tables 2, 3, and 4 respectively. For every region, there are four distinct models for each year and income group with the census tract (CT) serving as the unit of analysis. The dependent variable for these regressions is the percentage of PT mode share. The R-squared values range from 0.61 to 0.72 in 2016 and from 0.50 to 0.61 in 2021. External influences and control variables related to COVID-19 that were less significant in 2016 could be impacting the goodness-of-fit of the models in 2021.

The values we used for accessibility were the percentages of accessible jobs for each income group rather than the absolute number of accessible jobs to enable comparisons across regions, income groups, and years. For example, accessing 100,000 jobs could mean a high level of accessibility in a region with a small total number of jobs, it could also mean a low level of accessibility in a region with a much higher total number of jobs. Dividing this absolute value of 100,000 by the total number of jobs in the region provides a more meaningful scale for assessment and comparison between regions. Proportional measures are also important for comparison between years. In the case of our research, improving accessibility by 1% in 2016 would mean increasing the absolute number of accessible jobs by a larger value compared to 2021, as the denominator (total number of jobs) is larger in 2016 than in 2021 due to the working from home policies implemented at the time of the data collection. In all the models, there is a statistically significant positive association between accessibility and PT mode share, but at different levels. The accessibility squared term in the models shows a negative impact on PT mode share, keeping all else constant. This finding aligns with the observations from Fig. 2, where the mode share increases with accessibility up to a certain threshold, after which the relationship becomes reversed. The decline in PT mode share at higher accessibility areas could be explained by a greater prevalence of active modes of travel in these areas around the regions' city centers.

Considering the quadratic relationship between the percentage of accessibility and PT mode share, it is important to note that the starting point from which accessibility is increased would have different effects on PT mode share. Increasing accessibility from 1 to 2% would not have the same impact as increasing it from 7 to 8% although both are an increase of 1%. For example, we take the low-income group in Toronto in 2021 and solve the quadratic equation by inserting the mean values for the constants. We find that the maximum value of accessibility that would give out the highest mode share is when 4.46% of the total number of jobs in the region is accessible by PT. This translates to access to 62,000 low-income jobs in Toronto, provided that the total number of jobs remains unchanged. At this point, the PT mode share would become 31.5%. In other words, the accessibility target that needs to be set to achieve the maximum possible ridership among low-income individuals in Toronto in the post-pandemic time is 62,000 jobs reachable by PT in 45 min in travel time. While this value can be specific for a point in time (2021) when working from home was generally on the high end, it can be used as a directive for later periods when including the knowledge about the changes in WFH. Such numbers can help PT authorities in understanding the consequences of service cuts or changes on ridership.

A comparison between 2016 and 2021 across all regions indicates that the coefficients for accessibility have decreased for both income groups, with a larger drop for low-income groups. This decline signifies that the role of accessibility in promoting PT use has become less

Table 2
Toronto PT mode share percentage regression model.

	2016				2021			
	Low-income		Other-income		Low-income		Other-income	
Predictors	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*
(Intercept)	**55.07** ***	43.39 – 66.75	**36.16** ***	27.02 – 45.30	**79.36** ***	67.32 – 91.39	**42.08** ***	33.57 – 50.60
Accessibility measures								
Access. to below 30 k jobs (%)	**16.46** ***	15.07 – 17.85						
Accessibility^2 (%^{2})	**-1.99** ***	-2.19 – -1.78						
Access. to above 30 k jobs (%)			**3.40** ***	3.00 – 3.80				
Accessibility^2 (%^{2})			**-0.13** ***	-0.15 – -0.11				
Access.to below 40 k jobs (%)					**8.22** ***	6.97 – 9.46		
Accessibility^2 (%^{2})					**-0.92** ***	-1.11 – -0.72		
Access.to above 40 k jobs (%)							**2.92** ***	2.52 – 3.32
Accessibility^2 (%^{2})							**-0.14** ***	-0.17 – -0.11
Built environment								
Population density (1000/km^2)	0.08	-0.05 – 0.21	**0.34** ***	0.24 – 0.44	0.07	-0.03 – 0.18	**0.23** ***	0.16 – 0.30
Distance to Station (km)	**-0.48** ***	-0.63 – -0.34	**-0.52** ***	-0.63 – -0.42	**-0.50** ***	-0.63 – -0.36	**-0.27** ***	-0.36 – -0.18
CT Population characteristics								
Work from home %	**-0.97** ***	-1.15 – -0.80	**-0.34** ***	-0.48 – -0.20	**-0.43** ***	-0.49 – -0.37	**-0.24** ***	-0.28 – -0.20
Age (avg.)	**-0.30** **	-0.50 – -0.10	-0.11	-0.27 – 0.04	**-0.66** ***	-0.86 – -0.46	**-0.31** ***	-0.45 – -0.17
Household size (avg.)	**-5.52** ***	-7.13 – -3.92	**-4.34** ***	-5.59 – -3.09	**-8.30** ***	-9.87 – -6.74	**-5.23** ***	-6.34 – -4.13
Observations	1139		1139		982		982	
R^2 / R^2 adjusted	0.614 / 0.612		0.613 / 0.611		0.501 / 0.498		0.557 / 0.554	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 3
Montreal PT mode share percentage regression model.

	2016				2021			
	Low-income		Other-income		Low-income		Other-income	
Predictors	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*
(Intercept)	6.31	-5.25 – 17.86	**22.16** ***	13.68 – 30.65	**59.62** ***	47.32 – 71.92	**36.61** ***	27.10 – 46.11
Accessibility measures								
Access. to below 30 k jobs (%)	**7.42** ***	6.65 – 8.20						
Accessibility^2 (%^{2})	**-0.44** ***	-0.50 – -0.37						
Access. to above 30 k jobs (%)			**1.56** ***	1.34 – 1.77				
Accessibility^2 (%^{2})			**-0.03** ***	-0.04 – -0.02				
Access.to below 40 k jobs (%)					**3.74** ***	2.99 – 4.50		
Accessibility^2 (%^{2})					**-0.17** ***	-0.22 – -0.11		
Access.to above 40 k jobs (%)							**1.52** ***	1.21 – 1.83
Accessibility^2 (%^{2})							**-0.03** ***	-0.05 – -0.02
Built environment								
Population density (1000/km^2)	**0.44** ***	0.26 – 0.63	**0.47** ***	0.34 – 0.61	**0.39** ***	0.22 – 0.57	**0.21** **	0.08 – 0.34
Distance to Rapid Transit Station (km)	**-0.66** ***	-0.78 – -0.53	**-0.44** ***	-0.53 – -0.35	**-0.67** ***	-0.82 – -0.52	**-0.31** ***	-0.43 – -0.20
Population characteristics								
Work from home %	**-1.11** ***	-1.33 – -0.89	**-0.76** ***	-0.92 – -0.59	**-0.40** ***	-0.48 – -0.33	**-0.23** ***	-0.29 – -0.17
Age (avg.)	**0.32** ***	0.14 – 0.49	-0.02	-0.15 – 0.11	**-0.49** ***	-0.68 – -0.30	**-0.30** ***	-0.45 – -0.15
Household size (avg.)	**3.09** *	0.74 – 5.43	-0.83	-2.56 – 0.90	**-5.75** ***	-8.12 – -3.39	**-4.76** ***	-6.60 – -2.92
Observations	944		944		817		817	
R^2 / R^2 adjusted	0.724 / 0.722		0.745 / 0.743		0.618 / 0.614		0.597 / 0.593	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 4
Vancouver PT mode share percentage regression model.

	2016				2021			
	Low-income		Other-income		Low-income		Other-income	
Predictors	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*	*Coef.*	*95% CI*
(Intercept)	**40.55** ***	27.66 – 53.43	**37.57** ***	28.55 – 46.58	**44.09** ***	29.94 – 58.24	**26.99** ***	18.50 – 35.48
Accessibility measures								
Access. to below 30 k jobs (%)	**5.91** ***	5.12 – 6.70						
Accessibility^2 (%^{2})	**-0.34** ***	-0.41 – -0.28						
Access. to above 30 k jobs (%)			**1.17** ***	0.94 – 1.41				
Accessibility^2 (%^{2})			**-0.03** ***	-0.03 – -0.02				
Access.to below 40 k jobs (%)					**4.11** ***	3.37 – 4.84		
Accessibility^2 (%^{2})					**-0.19** ***	-0.24 – -0.14		
Access.to above 40 k jobs (%)							**0.88** ***	0.65 – 1.12
Accessibility^2 (%^{2})							**-0.02** ***	-0.03 – -0.01
Built environment								
Population density (1000/km^2)	**-0.31** **	-0.52 – -0.09	0.02	-0.13 – 0.16	0.02	-0.17 – 0.20	0.08	-0.03 – 0.19
Distance to Rapid Transit Station (km)	**-0.54** ***	-0.71 – -0.36	**-0.38** ***	-0.50 – -0.27	**-0.51** ***	-0.70 – -0.32	**-0.28** ***	-0.39 – -0.16
CT Population characteristics								
Work from home %	**-0.24** *	-0.43 – -0.05	**-0.36** ***	-0.49 – -0.23	**-0.37** ***	-0.47 – -0.27	**-0.20** ***	-0.26 – -0.14
Age (avg.)	**-0.29** *	-0.52 – -0.06	**-0.19** *	-0.36 – -0.03	**-0.37** **	-0.60 – -0.15	**-0.18** *	-0.32 – -0.04
Household size (avg.)	-1.86	-3.75 – 0.02	**-4.93** ***	-6.25 – -3.61	**-2.45** *	-4.56 – -0.33	**-3.19** ***	-4.47 – -1.92
Observations	463		463		465		465	
R^2 / R^2 adjusted	0.665 / 0.660		0.694 / 0.689		0.565 / 0.559		0.517 / 0.510	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

impactful in 2021. For example, concerning the low-income group in Toronto, a 1% increase in accessibility around the mean (from 1.6% to 2.6%) would increase the PT mode share by 16.4% in 2016 but only 8.2% in 2021, keeping all else constant. This represents an 8.2% decrease in the impact of improving accessibility by 1% on PT mode share for the low-income. A similar trend is observed in Montreal and Vancouver, with decreases of approximately 3.6% and 1.8%, respectively, for the low-income group. It is important to stress that to increase the percentage of accessibility, increasing the number of accessible jobs would not be sufficient if it is evened out by the increase in the total jobs in the region. In other words, planning for accessibility needs to be more ambitious in terms of targets to achieve the targeted rebound in ridership and increase it as outlined in transport plans especially for low-income groups.

For the other-income groups, the change in accessibility impact on PT mode share between 2016 and 2021 is not as remarkable as for the lower-income groups. To start with, accessibility already had a much smaller impact on PT mode share for this group in 2016. For example, in Montreal, increasing accessibility to low-income jobs by 1% would result in a 7.42% increase in PT mode share while the same increase for other-income jobs would lead to only 1.56%, ceteris paribus. Comparing this figure to 2021, we find that increasing accessibility to other-income jobs would increase PT mode share by 1.52%, only 0.04% less than in 2016. A similar pattern is observed in Toronto and Vancouver, with 0.48 and 0.29 differences, respectively, between the coefficients of accessibility for the other-income jobs in 2016 and 2021. This analysis indicates that the influence of accessibility on PT mode share for other-income groups has remained relatively stable or has experienced only marginal changes between 2016 and 2021, while the impact on lower-income groups is more pronounced. In other words, planning to increase accessibility in other income areas will not return as many ridership as it will in low-income areas in 2021. Nevertheless, low-income areas became less receptive to accessibility changes and require higher accessibility targets to achieve the same levels of ridership increase that they could have achieved with lower accessibility changes in 2016.

Another spatial factor that was considered in the analysis is the distance to the closest rapid transit station which was used as a proxy for the availability of high-quality transit in CTs. As discussed by Cui et al. (2020) in 2021 and aligning with the findings of Cervero et al. (2010), the distances remained negatively associated with the PT mode share for all three regions and the two income groups in 2021. There were only marginal changes in the coefficients between 2016 and 2021. However, in both 2016 and 2021, the low-income groups' PT mode share is more negatively impacted by the increase in the distance to stations. In other words, CTs far away from rapid transit use PT less in general in both time periods at the same rates.

The control variables used in the models include the average age and household size of the CT population. In Toronto, a one-year increase in average age would decrease PT mode share by about 0.3% for the low-income in 2016, and by 0.66% and 0.31% for the low- and other-income workers respectively in 2021, all else equal. This aligns with previous findings that public transit use tends to decline with increasing age (Brown et al., 2016; Newbold and Scott, 2018). Vancouver has a similar pattern of decreased PT ridership with the advancement of age and more so for low-income workers. While this pattern is similar for Montreal in 2021, the results suggest a reversed effect in 2016 where a one-year advancement in age for the lower-income group increases their PT usage by 0.32%. This result requires further investigation as previous research in Montreal suggests that aging has a negative impact on PT usage; however, it had not considered the impact of income (Fordham et al., 2017).

The effect of average household size is different for each region, income group, and year. The general notion is that the larger the household size average in a CT, the less PT ridership, except for the low income in 2016 Montreal. In Toronto, the negative impact of a growing household on PT mode share has increased in 2021 for both income groups. In Vancouver, this impact has decreased for the other income in 2021. The impact remained negative in the way that the growth of household size average by one person would decrease PT mode share by 3.19%, while it would have decreased the mode share by 4.93% in 2016, ceteris paribus. In Montreal, the PT mode share increases with a growing low-income household size in 2016 but this effect is reversed in 2021. This phenomenon can be explained by many factors including the different travel needs for children and older adults in a household and would require further investigations for Montreal in 2021. The WFH coefficients suggest that the increase in the percentage of WFH employees in the CT decreases the percentage of employees commuting by transit across all income groups and over time. This impact is stronger for low-income groups than other-income ones in both 2016 and 2021, which suggests that telecommuting replaces more PT trips for low-income groups than other-income ones. Due to the limitation imposed by the lack of census data that describe the number of workers from home in each income group, it is difficult to fully examine the impact of telecommuting on mode share using the available dataset.

6. Conclusions

Our research investigated the changing impacts of accessibility on PT mode share at the CT level of analysis for low- and other-income workers in the three largest metropolitan regions in Canada: Toronto, Montreal, and Vancouver. Using 2016 and 2021 census data, we find that there are major differences in the effect of accessibility on PT mode share pre- and post-pandemic. Our findings indicate that in 2021, low-income groups still use PT at a higher rate than other-income groups, as found in previous research (Cui et al., 2020; Giuliano, 2005). Increasing accessibility to jobs by PT remains to have a positive influence on PT mode share (Moniruzzaman and Páez, 2012; Owen and Levinson, 2015). However, the strong impact that was observed in 2016 has significantly decreased in 2021. For the low-income groups, that impact has declined by approximately 50% in Toronto and Montreal and by 30% in Vancouver. As the relationship between accessibility and PT mode share is quadratic (Cui and El-Geneidy, 2019), increasing accessibility is only useful until a certain threshold that needs to be carefully calculated before it starts becoming ineffective.

As PT agencies around the world try to attract the users back and balance their budgets through changes in service, service cuts (decrease in accessibility) would have a statistically significant negative impact on PT ridership. Service additions in 2021 will need to be more assertive, as the change in accessibility that was targeted in 2016 will not lead to the same increase in 2021 especially among low-income users, who are the core riders. Other income groups are still impacted by accessibility in 2021 like 2016, yet the impact is much lower when compared to the impacts of the same change in accessibility on low-income groups. We found that telecommuting is more likely to be replacing transit trips for low-income groups than other groups. It is important to note that while the magnitude of the impact of telecommuting has decreased, the average percentage of telecommuting has increased in all regions. Such coefficients need to be interpreted with the changes in the mean values in mind due to the magnitude of the output on PT mode share. Similar to 2016, the general trend is that the increase in average age and household size has a negative impact on the PT mode share. However, the extent of this impact varies among different income groups.

Achieving higher ridership through accessibility-focused planning has become more challenging due to the pandemic's repercussions. Increased efforts are needed in transport planning, land-use zoning, and jobs distribution to achieve the mode share targets of each region that were set prior to the pandemic. As the recovery process continues, it becomes essential to develop adaptive transport strategies that address the evolving needs of various communities to promote equity and provide services to those in need the most. This paper has shown that targeting low-income areas with accessibility increase in the post pandemic era will lead to higher return on such investments compared to investing these services in other-income areas. Yet, it is important to note that planning for accessibility in 2021 requires to be more assertive to achieve the planned PT mode shares as the accessibility impacts in 2021 are lower than the ones from 2016. Future research can follow a different modeling approach to control for spatial and temporal effects through utilizing more detailed datasets for each region, including comprehensive information about travel behaviour of the inhabitants and not limited to commute only.

Author contribution statement

The authors confirm contribution to the paper as follows: Study conception and design: Negm & El-Geneidy; Data collection: Negm & El-Geneidy; Analysis and interpretation of results: Negm & El-Geneidy; Draft manuscript preparation: Negm & El-Geneidy. All authors reviewed the results and approved the final version of the manuscript.

CRediT authorship contribution statement

Hisham Negm: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ahmed El-Geneidy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Data availability

The data that has been used is confidential.

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