

Factors associated with future transit use intentions: Evidence from large, mid-sized, and small Canadian metropolitan areas

Thiago Carvalho , Ahmed El-Geneidy ^{*} 

School of Urban Planning, McGill University, Canada

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ABSTRACT

Public transit agencies face challenges in sustaining and rebuilding ridership amid lasting impacts from the COVID-19 pandemic, making it crucial to understand who plans to use transit and why. We examine factors associated with intention to use public transit in the next year across Canada (4-point Likert scale) and assess how they vary by metropolitan area size. Using data from the Canadian Mobility Survey (N = 16,955) covering 12 census metropolitan areas, we estimate four weighted binary logistic regression models (i.e., a pooled national model and three metropolitan-area-size-specific models). Our results show that intention is strongly associated with recent transit use and self-identified transit-user status, with non-users exhibiting low intention. Baseline intention is also lower in mid-sized and small metropolitan areas than in large ones, consistent with urban scale capturing broader differences in transit context. Beyond this, higher satisfaction, perceptions that service is improving, seeing transit as suitable for reaching desired destinations (perceived accessibility), and support for increased operating funding are consistently associated with higher intention, as do living near rapid transit and deeming a 20–35-min door-to-door transit trip as reasonable, especially in larger metropolitan areas. Car use functions as a strong barrier, particularly in mid-sized and small metropolitan areas, where driving shares are highest. Overall, similar factors are associated with intention across urban scales, but their strength varies, with mid-sized and small metropolitan areas facing greater structural and behavioral barriers. These findings are of interest to policymakers and transit planners interested in increasing and retaining ridership.

1. Introduction

Public transport systems around the world have faced increasing challenges in sustaining and growing ridership. In North America, these pressures have been particularly strong: reduced costs of driving, including lower gasoline prices and declining shares of carless households, have contributed to prolonged ridership declines (Erhardt et al., 2022; Lee and Lee, 2022; Taylor and Fink, 2013), and the COVID-19 pandemic further accelerated this trend as many choice riders adapted through remote work or shifted to alternative modes while disadvantaged users remained reliant on transit (Brough et al., 2021; Haider et al., 2023). These challenges play out across a diverse set of metropolitan areas that differ markedly in population size, transit network structure, and levels of car dependence (Lane, 2010; Maghelal, 2011). Recent evidence suggests that the factors encouraging transit ridership do not operate uniformly across cities and are likely to vary with urban scale (Diab et al., 2020).

A substantial body of research has explored the determinants of

transit ridership, highlighting the roles of service supply (Lyons et al., 2017; Redelmeier and El-Geneidy, 2024), fare structures (Sharaby and Shifan, 2012), telecommuting (Abdollahpour et al., 2025; Carvalho and El-Geneidy, 2024), the built environment (Guerra and Cervero, 2011; Ma et al., 2018), and socio-demographic characteristics (Driscoll et al., 2018) in shaping demand. A complementary strand of research has focused on intention to use transit, typically within the broader context of transit loyalty, reflecting current users' willingness to keep using transit rather than broader intentions across the full population and emphasizing how travel satisfaction (De Oña et al., 2015; Hsieh, 2023), perceived service quality (Fu et al., 2018; Minser and Webb, 2010), and travel-related attitudes (Fu and Juan, 2016) shape future use intentions among users. Taken together, these strands show that transit use and repeat-use intentions are shaped by a combination of service conditions, personal characteristics, and psychological factors.

Building on this literature, the present paper focuses on future intention to use transit as an important outcome for understanding current and potential ridership. Consistent with the theory of planned

* Corresponding author.

E-mail addresses: thiago.carvalhodosreissilveira@mail.mcgill.ca (T. Carvalho), ahmed.elgeneidy@mcgill.ca (A. El-Geneidy).

behavior, intention is generally understood as an important predictor of behavior (Ajzen, 1991, 2011), although intentions do not always translate into observed behavior, particularly when adoption requires changes to established travel habits (Balaghi et al., 2026; Carvalho and El-Geneidy, 2026). Despite existing work on ridership and loyalty, several questions remain open. First, studies of intention to use transit have predominantly focused on current users, treating intention as a measure of loyalty and leaving less understood how future transit intention is shaped across the broader population, including non-users. Second, empirical analyses of intention have typically focused on a single city or network, with relatively few multi-city studies (De Oña, 2021; Kawabata et al., 2020; Vicente et al., 2020), most of which estimate models at an aggregate level without examining differences across cities or urban scales. Third, factors such as perceived accessibility, residential self-selection, and tolerable travel time (Cao et al., 2009; Guan et al., 2020; Milakis et al., 2015; Negm and El-Geneidy, 2025), while conceptually relevant to how people evaluate and choose travel options, have, to our knowledge, seldom been examined jointly as factors influencing transit intention in a national, multi-city setting. Together, these gaps limit our understanding of whether the correlates of future transit intention are broadly transferable or whether they vary across metropolitan contexts with different scales, network structures, and levels of car dependence.

This paper addresses these gaps by examining factors associated with future intention to use public transit across twelve Canadian census metropolitan areas (CMAs) using data from the Canadian Mobility Survey (N = 16,955). First, it extends the literature on transit intention beyond its usual focus on loyalty among current users by examining future transit intention across the broader population, including both users and non-users. Second, it explicitly assesses whether the factors associated with intention differ across large, mid-sized, and small CMAs, thereby exploring the extent to which urban scale influences how factors associated with future transit intention vary across metropolitan contexts. Specifically, the paper asks two research questions: (i) *What are the key factors associated with intention to use public transit in the near future in Canadian CMAs?* and (ii) *How do the strength and significance of these factors vary across metropolitan areas of different sizes?*

To answer these questions, we estimate four weighted binary logistic regression models: a pooled national model and three models stratified by CMA size. The models incorporate attitudinal and satisfaction measures, indicators of transit identity and current usage, proximity to rapid transit, perceived accessibility, tolerable travel time, residential self-selection, and socio-demographic characteristics. In doing so, the paper provides comparative evidence on the factors associated with intention to use transit across Canadian metropolitan areas and highlights policy levers that may need to be tailored to different urban scales rather than relying on a one-size-fits-all approach.

2. Literature review

This section reviews existing research on public transit use, focusing first on the determinants of transit ridership and then on the determinants of intention to use transit. Together, these strands of literature inform the selection of explanatory variables and provide the conceptual basis for the empirical analyses that follow.

2.1. Determinants of transit ridership

Many researchers have examined the determinants of transit ridership, particularly in efforts to understand the factors underlying ridership declines in North America during the 2010s. Service supply consistently appears as a key determinant of transit ridership across a variety of urban environments (Boisjoly et al., 2018; Diab et al., 2020; Erhardt et al., 2022). In an analysis of 152 urbanized areas across the United States, Lyons et al. (2017) find that although both frequency and route density have significant and positive effects, the impact of

frequency is stronger: a 10% increase in frequency predicts about a 9.3% ridership gain, compared to 6.9% for a 10% increase in route density. These results suggest that, under constrained budgets, agencies should prioritize higher frequency on key corridors over thinner, broader coverage. Increases in service supply have also been found to mitigate the negative effects of reduced costs of driving on transit ridership in the United States (Lee and Lee, 2022). Lower fuel prices, in particular, exert a significant and negative influence on transit ridership (Lane, 2010; Maghelal, 2011), although effects vary by mode, with smaller impacts on rail-based transit (Haire and Machemehl, 2010) and lower-income individuals tend to be more sensitive to price-related elasticities of demand (Jung et al., 2016).

Beyond service and macroeconomic factors, several other elements have been found to have a negative effect on ridership. Fare increases have been shown to reduce ridership (Brown and Thompson, 2008; Guerra and Cervero, 2011; Haire and Machemehl, 2010), underscoring the importance of fare reductions and fare-capping programs for expanding the market (Tabassum et al., 2025). Higher crime rates are associated with lower ridership (He and Li, 2025). In an analysis of the five largest cities in Texas, Li et al. (2025) find that the relationship between crime and ridership is non-linear, following an inverted U-shape: ridership rises with crime at low levels but declines beyond a threshold of 12 crimes per capita. Crime also weakens the effects of service supply, with investments on frequency yielding smaller gains in higher-crime areas. Broadly, ridership is also affected by seasonality, peaking during school terms and falling sharply during Christmas and summer holidays (Kashfi et al., 2015).

The effects of ride-hailing and micromobility on transit ridership appear to be mixed. In an analysis of 103 transit agencies across Canada from 2002 to 2016, Diab et al. (2020) find that Uber's presence had a modestly complementary effect in large systems but a substitutive one in small systems. Across the United States, Lee and Lee (2022) identify minor effects from the introduction of ride-hailing services, with slight substitution for bus services and complementary effects for rail. Using a difference-in-differences design comparing 2014 and 2019 ridership levels, Choi and Park (2025) find a negative but not significant effect of bike-sharing systems on transit ridership, while scooters exhibit a significant substitution effect. The authors highlight the need for agencies to integrate shared micromobility services into their networks so that they support rather than compete with transit. On that note, there is evidence that e-bikes have a stronger substitution effect on transit ridership than free-floating and station-based pedal bikes (Liu et al., 2025), and that bike-sharing systems are more likely to compete with transit on short, direct trips than on longer routes (Godavarthy et al., 2022).

The built environment is another key lever of transit ridership, with higher residential and employment density, mixed land use, and walkability generally associated with higher ridership (Guerra and Cervero, 2011; Li et al., 2025; Rahman et al., 2021). Overall, uniform land use tends to produce sharper peak periods, while mixed-use development disperses demand more evenly throughout the day (Kim and Jang, 2022). The strength of built-environment effects is time-of-day dependent (Gan et al., 2020; Ma et al., 2018), with employment densities particularly associated with weekday and peak-period trips (Li et al., 2020). Socio-demographic characteristics also play a well-documented role, with students, lower-income households, renters, and immigrants, particularly in smaller cities, being more likely to use transit, while higher-income individuals and older adults are less likely (Diab et al., 2020; Erhardt et al., 2022; Kerkman et al., 2019; Li et al., 2025; Rahman et al., 2021; Tiznado-Aitken et al., 2024).

Urban scale has also been identified as an important contextual factor shaping transit ridership. In this sense, it serves as a proxy for a broader set of conditions that tend to support transit use. In a study of 265 urbanized areas in the United States, Taylor et al. (2009) show that variation in transit use is strongly associated with metropolitan characteristics such as population size, density, and land area, and that larger

and denser urbanized areas tend to exhibit higher ridership. This pattern likely reflects the tendency of larger metropolitan areas to have higher densities, more concentrated activity patterns, and more extensive transit networks, which together make fixed-route transit more viable (Cervero and Guerra, 2011; Taylor and Fink, 2013; Wu et al., 2019). Relatedly, Wu et al. (2019) show that larger metropolitan areas obtain higher returns from transit accessibility improvements, suggesting that ridership effects are stronger in places with more mature transit systems and a larger existing ridership base. Moreover, Diab et al. (2020) indicate that several determinants of ridership, including built environment, gas prices, and ride-hailing effects, differ between larger and smaller transit agencies. At the same time, urban scale alone is not sufficient, as its effects on ridership depend on how metropolitan size translates into density, service provision, and accessibility (Merlin et al., 2021).

The COVID-19 pandemic brought about significant structural shifts, leading to prolonged declines in transit ridership compared to other recent large-scale disruptive events, such as terrorist attacks and other epidemic/pandemic events (Liu et al., 2023). Telecommuting has continued to suppress recovery (Tiznado-Aitken et al., 2024; Ziedan et al., 2023), with higher-income, middle-aged adults especially less likely to have returned to transit (Kutela et al., 2025). Importantly, service frequency appears to have become an even stronger determinant of ridership. In a study of Montreal's bus service before and after the pandemic, Redelmeier and El-Geneidy (2024) find that a 10% change in trips is associated with about a 13% change in ridership pre-COVID and 15% post-COVID, implying steeper losses if frequency is cut.

Overall, this literature provides a rich account of how socio-demographic characteristics, built environments, service conditions, broader structural changes, and urban scale shape transit use. In particular, this literature suggests that city scale is important because it captures differences in the urban contexts within which transit operates. However, most of this research focuses on actual ridership, with limited attention to the psychological and motivational processes that underlie future use. Because any shift in ridership ultimately depends on individuals' intentions to use transit, it is important to complement these ridership-based studies with research on the determinants of intention to use transit.

2.2. Determinants of intention to use public transit

Intention to use transit has mostly been examined within the broader construct of transit loyalty. Loyalty is a multidimensional concept that has been operationalized in different ways in the literature, often through one or more indicators such as willingness to reuse and willingness to recommend transit (Carvalho et al., 2022). In this context, intention to use transit is typically measured among existing users and reflects their stated intention to keep using transit in the future. Thus, in much of the transit literature, future use intention is treated as one dimension or indicator of loyalty among current users, although some studies use reuse intention as a direct proxy for loyalty (De Oña et al., 2015; Kim and Ulfarsson, 2012; Sun and Duan, 2019; Tao et al., 2017). As such, this literature focuses primarily on retention intention rather than adoption intention. Among non-users, however, intention to use transit reflects a different process: the willingness to start using transit, which may involve reconsidering established travel routines and overcoming habitual reliance on other modes.

Empirically, the loyalty literature has largely focused on specific transit networks (Fu and Juan, 2016; Lai and Chen, 2011; Park et al., 2021; Sun et al., 2021) or particular modes within a network (Allen et al., 2019; Chen, 2016; Kim and Ulfarsson, 2012), with relatively few studies examining factors shaping reuse intentions across multiple cities or across cities of different sizes. Even in the limited number of multi-city studies, analyses are rarely disaggregated by city or region. Vicente et al. (2020), for example, found that environmental sustainability attitudes positively influence transit satisfaction and willingness to reuse across 18 municipalities in the Greater Lisbon region, but

estimated their models at the aggregate level. Similarly, Kawabata et al. (2020) analyzed longitudinal data from four European cities to examine relationships between service quality, satisfaction, loyalty, and frequency of use, again deriving models at the aggregate level.

The loyalty literature has been strongly influenced by satisfaction research, although socio-psychological constructs, such as attitudes and social norms, have increasingly been incorporated, reflecting growing recognition of the psychological and motivational factors influencing the success of transport policies (Donald et al., 2014). Within this literature, previous research has shown that travel satisfaction strongly shapes behavioral intentions (Van Lierop et al., 2018), consistent with the idea that travelers seek to maximize the utility they derive from travel (De Vos et al., 2016; Ye and Titheridge, 2016). Satisfaction, and by extension behavioral intentions, are influenced by perceptions of service quality and perceived value, which often act in tandem in the development of service perceptions (Cronin et al., 2000). Travel satisfaction has also been identified as an important driver of positive travel-related attitudes, which in turn influence modal choice (De Vos et al., 2016; Diana, 2012). De Vos and Witlox (2017) describe the existence of a continuous, non-recursive relationship between satisfaction and attitudes, with travel satisfaction playing a key role in shaping travel-related attitudes over the longer term. Together, these findings highlight the significant role of travel satisfaction in shaping both how people feel about travel and how they travel.

In parallel to the satisfaction-based understanding of behavioral intentions, socio-psychological frameworks such as the theory of planned behavior emphasize attitudes, social norms, and perceived behavioral control (PBC) as key determinants of behavioral intentions (Ajzen, 1991, 2011). Attitudes reflect an inclination towards a given behavior based on salient beliefs and have been shown to influence mode choice (Johansson et al., 2006; Ye and Titheridge, 2016); for instance, the attractiveness of driving exerts a strong negative influence on transit intentions (Li et al., 2018). Social norms relate to perceived social pressure to perform a behavior, while PBC captures individuals' perceptions of the resources, opportunities, and constraints involved in enacting that behavior. For stable, repeated behaviors, however, habit can weaken the influence of attitudes, social norms, and PBC and inhibit the formation of new behaviors (Chen and Chao, 2011) acting as a barrier for change (Friedrichsmeier et al., 2012; Verplanken et al., 2002) and to the processing of new and relevant information (Gärling and Axhausen, 2003).

Taken together, satisfaction-based and socio-psychological studies offer insight into how experience- and belief-based factors influence intentions, but they have predominantly been applied to current users and to specific urban or modal contexts. As a result, we still lack a clear understanding of how factors associated with intention operate across the wider population, including non-users, and how they differ across cities of different sizes, where variations in scale, network structure, and car dependence are likely to require different levers for encouraging transit use. Considering these gaps, this paper examines factors associated with future intention to use transit across 12 Canadian metropolitan regions (CMAs) and separately for large (≥ 1.5 million), mid-sized (500,000–1.5 million), and small ($< 500,000$) CMAs, to assess how these factors vary with urban scale.

3. Data & methods

3.1. The Canadian Mobility Survey

The Canadian Mobility Survey (CMS) is a bilingual online survey administered by the Transportation Research at McGill (TRAM) research group across twelve Canadian census metropolitan areas (CMAs): Toronto, Montreal, Vancouver, Ottawa–Gatineau, Calgary, Edmonton, Québec, Winnipeg, Hamilton, Halifax, Victoria, and Saskatoon (listed here in order of population size) in Fall 2024. The CMS collects detailed information on transit perceptions, transit satisfaction, travel behavior,

and socio-demographic characteristics. To ensure a large and diverse sample, multiple recruitment strategies were employed, including data collection through a specialized marketing firm (Leger), social media campaigns, flyer distribution, and personalized email invitations, following best practices outlined by Dillman et al. (2014).

To ensure data quality, a multi-step cleaning strategy was applied. Respondents were excluded based on unrealistically short completion times, incomplete responses, or multiple submissions from the same email address. Submissions from the same IP address were retained only when the IP appeared twice with different email addresses. Respondents who placed their home, school, and/or work locations outside their selected CMA or in water bodies were also removed. Full details on the survey instrument and cleaning process are provided in Negm et al. (2025b).

For the present analysis of the drivers of intention to use public transit, we use the full cleaned and validated sample. The CMS comprises 16,955 respondents, with sample sizes exceeding 1,000 respondents in each CMA except Saskatoon ($N = 773$). To account for sampling imbalances and increase representativeness, survey weights were derived separately for each CMA using the *anesrake* R package (Pasek, 2018), which implements an iterative raking procedure (DeBell and Krosnick, 2009). The weights were calibrated to match 2021 CMA-level Census distributions of age, income, gender, and commute mode shares at the census tract level, obtained from Statistics Canada (2023) via the *cancensus* R package (von Bergmann et al., 2021). Before weighting, the sample exhibited some deviations from 2021 CMA population profiles that varied across regions, including a tendency to overrepresent women, working-age adults, and employed respondents, while underrepresenting older adults and lower-income households in several CMAs (Negm et al., 2025b). Although the weighting procedure was designed to reduce these imbalances, some residual sampling bias may remain. The results should therefore be interpreted in light of the limitations of a non-probability sample.

Because the twelve CMAs encompass a wide range of urban sizes, we stratify them into three groups that reflect differences in population scale and transit network structure: (i) large CMAs with populations of 1.5 million or more (Toronto, Montreal, Vancouver), which together account for about 70% of national transit trips (APTA, 2025) and comprise extensive multimodal transit networks; (ii) mid-sized CMAs with 500,000–1.5 million residents, which generally have substantial but less extensive transit systems, most with existing or planned BRT and/or LRT networks (e.g., the O-Train in Ottawa–Gatineau, C-Train in Calgary, the Capital, Metro, and Valley lines in Edmonton, the planned Québec City Tramway, Winnipeg Rapid Transit, and the planned HSR Next in Hamilton); and (iii) small CMAs with fewer than 500,000

residents, which are primarily served by bus-based transit systems. This stratification is illustrated in Fig. 1.

3.2. Modeling approach

Intention to use public transit within the next year was measured using a self-report item (“I plan to use public transit in my region within the next year”) rated on a four-point Likert scale from strongly disagree to strongly agree. The dependent variable captures respondents’ self-reported intention to use existing public transit in their region within the next year, rather than preferences toward a hypothetical new service or scenario. Moreover, direct self-reported future-use intention measures are common in the transit literature, where they are often used to examine continued use, loyalty, or intended adoption of transit services (Diab et al., 2017; Sener et al., 2020; Tao et al., 2017). For the main analysis, this variable was recoded into a binary indicator distinguishing respondents who intend to use public transit (agree or strongly agree) from those who do not (disagree or strongly disagree). This specification was adopted to capture a clear and policy-relevant contrast between respondents with and without a stated intention to use transit. Although this dichotomization reduces variation in the original ordinal response scale, ordered probit models estimated as a robustness check yielded substantively similar conclusions and are reported in the Appendix (Table A1).

Among current users, the indicator captures the respondents’ intention to continue using transit and is therefore related to the notion of loyalty; this distinction is addressed in the models through controls for self-identified transit user status and transit use frequency. We estimate four weighted binary logistic regression models (i.e., a pooled national model and three models stratified by CMA size) to assess how the correlates of intention vary with urban scale. Survey weights were applied to account for sampling biases in the survey data; the weighting strategy is described in the previous section.

Predictors were selected based on factors identified in the literature review and on their availability in the CMS, including variables related to attitudes, satisfaction, travel behavior, telecommuting frequency, the transit network, residential self-selection, built environment, and socio-demographic characteristics. The models retain theoretically relevant controls even when they are not statistically significant, to avoid specification decisions based solely on statistical significance. Table 1 summarizes the explanatory variables, their wording, and coding.

Because several predictors either extend beyond what is commonly examined in the literature or require more specific operationalization, we briefly elaborate on them here. In relation to the transit network, we retain variables capturing proximity to rapid transit (e.g., metro and LRT

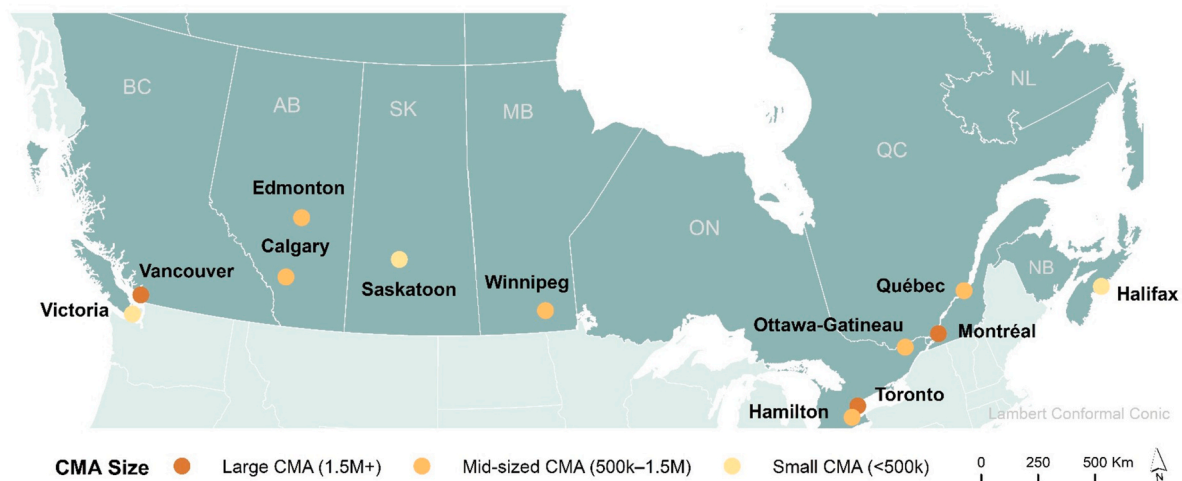


Fig. 1. Cities surveyed in the Canadian Mobility Survey by size of the metropolitan area.

Table 1
Modeled explanatory variables.

Dimension	Variable	Descriptive
Attitudes	Transit identity	I consider myself a transit user [Binary: Yes/No]
	Essential service	Public transit is an essential service to society [4-point Likert scale]
	Service improvement	In the last 12 months, the public transit services I use have ... [Gotten much worse; Gotten a bit worse; Stayed the same; Gotten a bit better; Gotten much better]
	Support for funding	Do you support increasing funding for operating public transit by 5% in your region in order to maintain and improve the current service? [Binary: Yes/No]
Tolerable travel time	Reasonable travel time by transit	What is a reasonable door-to-door travel time by public transit to reach your desired destinations (e.g., grocery stores, shopping, gyms, restaurants, pharmacies, etc.)? [Categorical: ≤15; 20 - 35; 40 - 60; >65 min]
Perceived accessibility	Suitable to reach desired destinations	Public transit is a suitable mode of travel for me to reach my desired destinations [4-point Likert scale]
Satisfaction	Transit satisfaction	Overall, I am satisfied with the public transit services in my region [4-point Likert scale]
	Transit usage	Categorical variable [Used in the past week; Used in the past year; Non-user]
Travel behavior	Owens a bicycle	I own a bicycle [Binary: Yes/No]
	Driving share	Share of car trips during the past 7 days
	Metro access	Metro access within 600 m from their home location [Binary: Yes/No]
Transit network	LRT access	LRT access within 400 m from their home location [Binary: Yes/No]
	Being near transit selection	When you moved into your current home, how important were the following factors in your decision? [Being near public transportation] [5-point Likert scale]
Residential self-selection	Being near cycling infrastructure	When you moved into your current home, how important were the following factors in your decision? [Being near bicycle infrastructure] [5-point Likert scale]
	Age	Continuous variable [Age in 2024]
Socio-demographic	Gender	Binary variable [Men/Women]
	Household size	Categorical variable [One; Two to Four; Five or more individuals]
	Household income	Binary variable [Below/Above the average of regional median household income (CAD 90k)]
Employment	Immigrant	Binary variable [Yes/No]
	Worker	Binary variable [Yes/No]
	Student	Binary variable [Yes/No]
Built environment	Telecommuting	Continuous variable [Telecommuting frequency: 0-7 days]
	WalkScore®	Categorical [Car-dependent, 0 - 49; Somewhat walkable (50 - 69); Walkable (70 - 100)]

access) to assess how access to higher-frequency transit affects behavioral intention. Proximity is operationalized as binary indicators for metro within 600 m and LRT within 400 m of the home location; these thresholds were selected following exploratory tests with continuous and banded distance measures, which indicated that associations with intention attenuate beyond approximately 600 m for metro and 400 m for LRT. In addition, we include a measure of perceived accessibility, reflecting individuals' perceptions of how easily they can reach desired destinations by public transit (Negm et al., 2025a), which, while underexplored, has been shown to positively influence transit mode

share (Negm and El-Geneidy, 2025). We also include a measure of tolerable travel time, given its documented influence on user experiences with transit (Carvalho and El-Geneidy, 2025). Finally, to account for regional heterogeneity, the national model includes dummy variables for CMA size (large, mid-sized, and small CMAs), while the size-stratified models include CMA-specific dummy variables (with one CMA per group serving as the reference category).

3.3. Weighted descriptive statistics

Table 2 reports the weighted descriptive statistics at the national and CMA group levels for the exploratory variables. Descriptive statistics on the dependent variable are introduced in the Results section. After

Table 2
Weighted descriptive statistics by CMA size.

Variables	National	Large CMA	Mid-sized CMA	Small CMA
Socio-demographic				
Gender				
Women	52.5%	52.7%	52.0%	52.5%
Age				
18-35	31.6%	31.9%	31.1%	30.5%
36-64	48.5%	48.3%	49.1%	47.8%
65 and over	19.9%	19.9%	19.8%	21.7%
Income				
< 60k CAD	31.7%	32.4%	29.0%	33.9%
60 to 120k CAD	36.2%	35.7%	37.3%	37.6%
> 120k CAD	32.2%	31.9%	33.7%	28.6%
Household size				
One	23.0%	23.3%	22.3%	21.7%
Two to Four	69.0%	68.2%	70.9%	72.3%
Five or more	8.0%	8.4%	6.8%	6.0%
Immigrant (%)	25.9%	28.3%	19.8%	17.8%
Employment				
Worker	66.9%	66.4%	68.7%	65.6%
Student	9.3%	9.4%	8.9%	10.1%
Telecommuting frequency ^b	1.1 (1.8)	1.1 (1.9)	1.0 (1.7)	0.8 (1.6)
Transit identity and perceptions^a				
Transit user	44.3%	50.0%	29.7%	27.3%
Transit satisfaction	53.1%	58.8%	38.4%	37.1%
Essential service	96.7%	97.3%	95.4%	94.8%
Suitable to reach desired destinations	49.1%	54.6%	35.1%	33.5%
Service improvement	8.3%	8.8%	7.1%	5.6%
Support for funding	67.4%	67.5%	66.6%	72.0%
Transit usage				
Used in the past week	37.7%	43.2%	23.9%	20.3%
Used in the past year	39.6%	40.4%	37.7%	37.4%
Non-user	22.6%	16.4%	38.4%	42.3%
Proximity to rapid transit				
Metro [<600 m]	7.0%	9.6%	0.0%	0.0%
LRT [<400 m]	4.9%	6.3%	1.5%	0.0%
Reasonable travel time by transit				
≤15 min	28.8%	29.5%	27.1%	26.6%
20 - 35 min	52.4%	52.1%	53.2%	53.5%
40 - 60 min	13.6%	13.6%	13.6%	13.3%
>65 min	5.2%	4.8%	6.1%	6.6%
Travel behavior				
Owning a bicycle	51.6%	50.5%	55.7%	45.0%
Driving share [Past 7 days] ^b	68% (36.2%)	65% (37.3%)	75.8% (31.7%)	76% (30.9%)
Residential self-selection				
Being near transit	50.4%	54.8%	39.2%	34.8%
Being near cycling infrastructure	19.9%	19.6%	21.5%	15.4%
Urban Environment: Walk Score®				
Car-dependent, 0 - 49	23.6%	19.5%	34.0%	35.3%
Somewhat walkable (50 - 69)	21.8%	20.3%	26.3%	22.1%
Walkable (70 - 100)	54.6%	60.1%	39.7%	42.6%

^a Agreement with the statement.

^b Mean (Standard deviation).

applying survey weights to match census distributions, the weighted CMS sample is slightly skewed toward women (52.5%), with very similar gender shares across CMA size groups. The weighted age profile is dominated by middle-aged adults (36–64 years; 48.5%), followed by younger adults (18–35 years; 31.6%), while older adults (65+ years) represent about one fifth of respondents (19.9%); smaller CMAs show a modestly higher share of older adults (21.7%). Household income is weighted toward the middle-income category (60–120k CAD), which accounts for 36.2% of respondents nationally, although smaller CMAs exhibit higher shares of lower-income households (<60k CAD: 33.9%) and lower shares of high-income households (>120k CAD: 28.6%). Most respondents live in households of two to four individuals (around 69% nationally, with only minor variation across CMAs), while single-person households account for about 23% and larger households (five or more) for 6–8%. Finally, immigrants account for 25.9% of respondents overall, with higher representation in large CMAs (28.3%) and lower shares in mid-sized and small CMAs (19.8% and 17.8%, respectively).

Employment-related characteristics show relatively limited variation across CMA sizes. Overall, 66.9% of respondents are workers, with similar shares across large, mid-sized, and small CMAs. Students represent 9.3% of the weighted sample nationally, with only slightly higher representation in small CMAs (10.1%). Telecommuting frequency is also fairly similar across groups, averaging 1.1 days per week nationally, though somewhat lower in small CMAs (0.8 days).

In the weighted sample, 44.3% of respondents identify as transit users, with a higher share in large CMAs (50.0%) and much lower shares in mid-sized (29.7%) and small CMAs (27.3%). These patterns are consistent with reported transit use: nationally, 37.7% used transit in the past week and 39.6% used it in the past year, while 22.6% report not having used transit at all, with large CMAs showing higher proportions of frequent users and mid-sized and small CMAs higher proportions of non-users. This pattern is consistent with previous research showing that larger metropolitan areas tend to support higher transit ridership because of their greater density, more concentrated activity patterns, and more extensive transit networks (Taylor and Fink, 2013).

Perceptions of transit are generally more favorable in large CMAs than in mid-sized and small CMAs. Nationally, 53.1% of respondents report being satisfied with transit services, but this rises to 58.8% in large CMAs and falls below 40% in mid-sized and small CMAs. About half consider transit suitable for reaching their desired destinations, with higher perceived accessibility in large CMAs (54.6% versus 35–34% in mid-sized and small CMAs). Perceptions of recent service improvement are modest overall but again more positive in large CMAs (8.8% versus 7.1% and 5.6%). Support for increasing operating funding is relatively similar across CMA sizes, ranging from 66.6% in mid-sized to 72.0% in small CMAs.

Across all CMA sizes, respondents converge around a similar notion of tolerable travel time by transit, with just over half considering 20–35 min reasonable (52.4%), in line with thresholds identified in previous research (Carvalho and El-Geneidy, 2025; Milakis et al., 2015; Milakis and van Wee, 2018). Travel by car also varies by CMA size: the average driving share over the past seven days is lower in large CMAs (65%) and higher in mid-sized and small CMAs (around 76%).

Active and transit-supportive orientations also differ by CMA size. Bicycle ownership is common overall (51.6%) and is slightly more prevalent in mid-sized CMAs (55.7%). Residential self-selection patterns mirror these differences: nationally, half of respondents (50.4%) report that being near transit was important when choosing their home, with higher shares in large CMAs (54.8%) than in mid-sized and small CMAs (39.2% and 34.8%). By contrast, mid-sized CMAs show the highest share of respondents who considered proximity to cycling infrastructure (21.5%, compared with 19.6% in large and 15.4% in small CMAs). This pattern should be interpreted cautiously, however, as cycling conditions vary across CMAs. In the studied regions, bicycle commute mode share is generally higher where bike-network quality is stronger and frost-free periods are longer, although this relationship is more mixed among

mid-sized CMAs.

Walk Score is included as a measure of walkability and local accessibility. This index has been repeatedly tested in the context of land use and transport literature (Hall and Ram, 2018) capturing the accessibility of everyday destinations within walking distance (Walk Score, 2026). Walk Score ranges from 0 to 100 and is commonly grouped into four categories: car-dependent (0–49), somewhat walkable (50–69), very walkable (70–89), and walker's paradise (90–100). For the purposes of this analysis, the two highest categories were combined into a single walkable category (70–100). The weighted descriptive statistics suggest that respondents in large CMAs tend to live in more walkable environments than those in mid-sized and small CMAs. Nationally, 54.6% of respondents are located in walkable areas, rising to 60.1% in large CMAs, compared with 39.7% and 42.6% in mid-sized and small CMAs, respectively. Conversely, car-dependent environments are more common in mid-sized and small CMAs (34.0% and 35.3%) than in large CMAs (19.5%).

4. Results & discussions

4.1. Regional differences

Before turning to the regression models, we first examine how intention to use transit varies by CMA size using tests that account for the survey weights. Because intention to use transit is a binary variable and the data are survey-weighted, a *t*-test or unweighted chi-square test would ignore the sampling design and risk understating uncertainty. Instead, we treat intention cross-tabulated by CMA size and apply the Rao–Scott F-adjusted chi-square test, which is a chi-square test adjusted for survey weights to assess the association between the two variables (Rao and Scott, 1984; Scott and Rao, 1981). Results are illustrated in Fig. 2.

Weighted intention to use transit declines systematically with CMA size: large CMAs show the highest proportion of respondents intending to use transit in the next year (76.3%; 95% CI 74.6–77.8), followed by mid-sized CMAs (52.0%; 95% CI 50.5–53.4) and small CMAs (45.7%; 95% CI 43.3–48.1). The Rao–Scott test strongly rejects equality across the three groups ($F = 309.4$, $p < 0.001$). To identify which groups differ, we conduct survey-weighted pairwise comparisons using Tukey-adjusted odds ratios (all Tukey-adjusted $p < 0.001$). These contrasts show a clear ordering, respondents in large CMAs have approximately 3.0 times the odds of intending to use transit compared with those in mid-sized CMAs and about 3.8 times the odds compared with those in small CMAs. These pre-model results reinforce the importance of CMA size and support estimating determinants of intention separately by size.

To further explore regional differences in transit intention, Fig. 3 disaggregates results by self-identified transit user status within each CMA size category. Across all CMA sizes, self-identified transit users are more likely than non-users to report intending to use transit in the next year. In large CMAs, 96.4% of transit users intend to use transit, compared with 56.7% of non-users. In mid-sized CMAs, the corresponding shares are 94.1% and 34.1%, while in small CMAs they are 89.8% and 28.0%, respectively. These figures show that the intention to use transit is consistently higher among current transit users across all regional contexts. Moreover, intention among non-users declines sharply as CMA size decreases. At the same time, the composition of the sample shifts across CMA sizes: those identifying as transit users account for 50.0% of respondents in large CMAs, compared with 29.7% in mid-sized CMAs and 27.3% in small CMAs. These patterns indicate that variation in transit intention across CMA sizes is associated both with the share of respondents who identify as transit users and with the willingness of non-users to consider future transit use.

4.2. Drivers of intention to use transit

Table 3 reports the weighted binary logistic regression models of

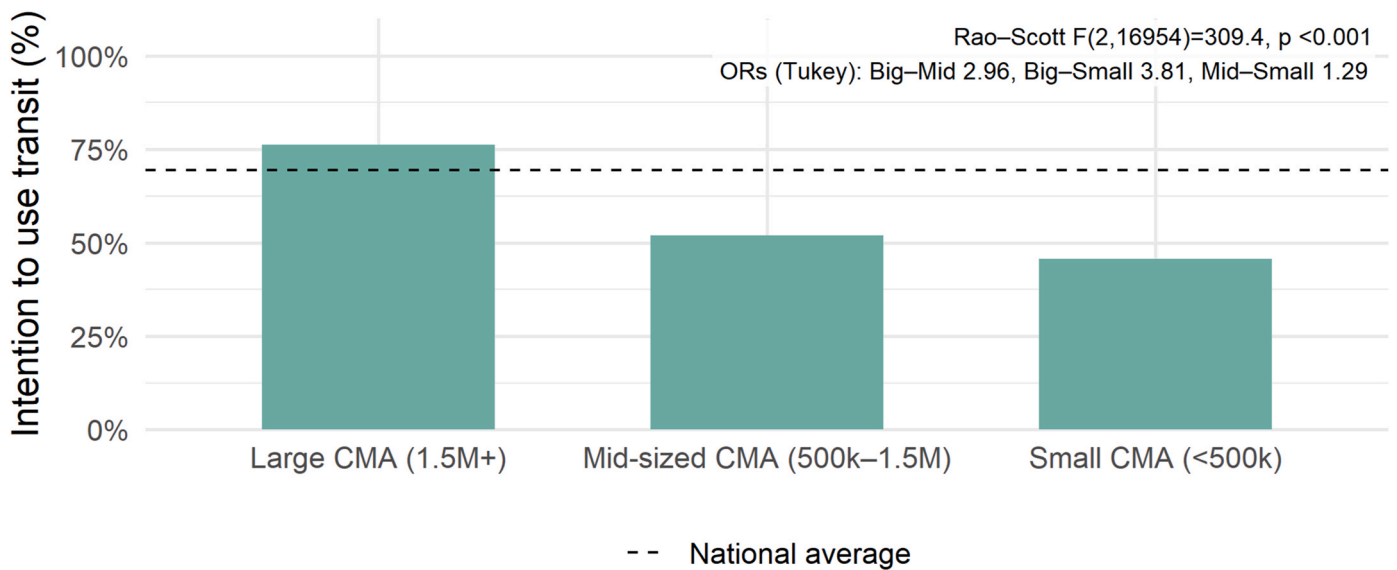


Fig. 2. Intention to use public transit by size of the metropolitan area.

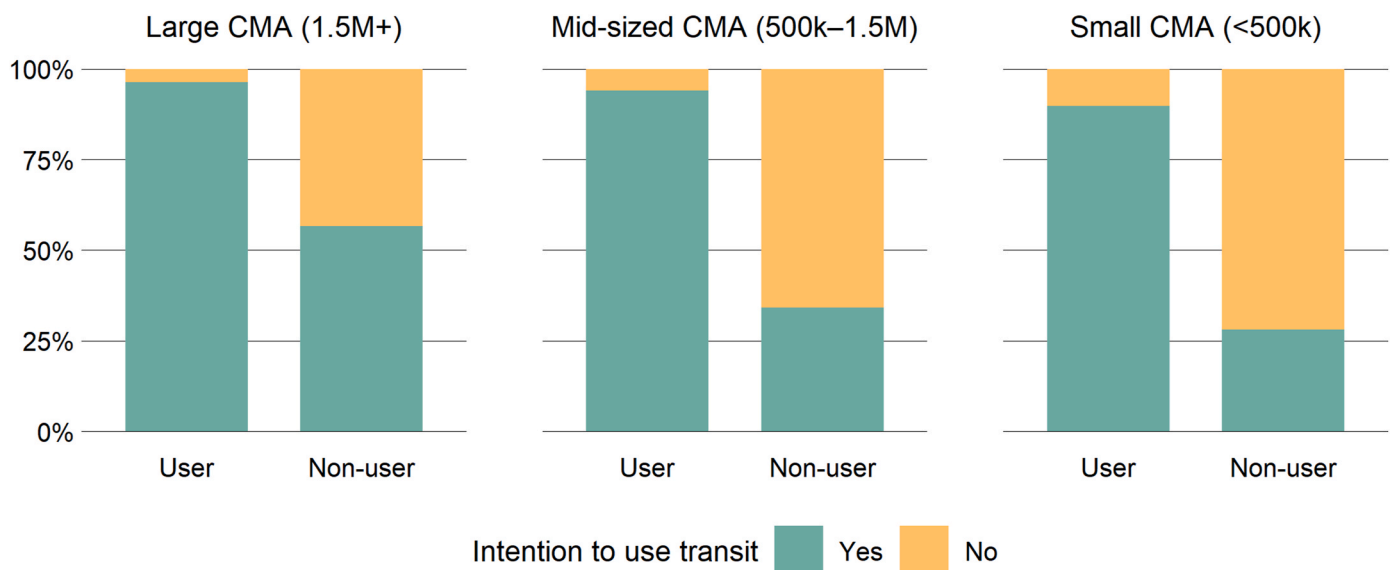


Fig. 3. Intention to use public transit by user identity and size of the metropolitan area.

intention to use public transit within the next year for the full national sample and separately by CMA size. Model fit is strong in all cases: Tjur's R^2 is 0.602 for the national model, 0.519 for large CMAs, 0.601 for mid-sized CMAs, and 0.594 for small CMAs, indicating that the selected variables account for a substantial share of the variation in intention. Multicollinearity does not appear to be a concern with maximum adjusted variance inflation factors (VIFs) ranging from 1.01 to 1.65, well below commonly used thresholds suggesting that the included attitudinal, behavioral, built environment and socio-demographic variables provide distinct information rather than capturing the same underlying constructs.

4.2.1. Transit identity and recent transit use

Transit identity and recent transit use emerge as some of the strongest correlates of intention to use transit. Nationally, respondents who identify as transit users have about 2.6 times the odds of intending to use transit in the next year compared with those who do not (OR = 2.56, 95% CI 2.08-3.16), with even stronger associations in mid-sized and small CMAs (OR = 3.63 and 3.04, respectively). Recent usage patterns

show an equally strong gradient across CMAs. Relative to respondents who used transit in the past week, those who used it only in the past year have roughly half the odds of intending to use transit (OR = 0.51-0.61 across CMA models), while non-users exhibit markedly lower odds in all models (OR = 0.05-0.06). Overall, these findings indicate that future transit intention is closely associated with both transit identity and recent transit use. These variables are included to capture respondents' existing relationship with transit at the time when future intention is reported.

As reflected in these findings, intention to use transit in the next year does not have the same interpretation for all respondents. Among current users, particularly frequent users, it is more closely aligned with retention intention and, more broadly, with one dimension of transit loyalty. For non-users, by contrast, it is better understood as adoption intention, that is, a willingness to begin using transit in the next year. This distinction is important when interpreting the results, as stated future intention should not be interpreted as equivalent to observed subsequent behavior, particularly among non-users, for whom intention reflects openness to adoption rather than actual mode switching.

Table 3
Binary logistic regression results.

Predictors	National		Large CMA		Mid-sized CMA		Small CMA	
	OR	CI	OR	CI	OR	CI	OR	CI
Intercept	4.08 ***	2.57 – 6.46	1.55	0.68 – 3.52	3.39 ***	1.70 – 6.81	7.19 ***	2.44 – 21.15
Transit identity								
Transit user	2.56 ***	2.08 – 3.16	1.91 ***	1.35 – 2.73	3.63 ***	2.86 – 4.62	3.04 ***	2.19 – 4.25
Transit user vs Gender [Women]	1.45 **	1.11 – 1.89	2.30 ***	1.45 – 3.67				
Transit satisfaction and perceptions								
Transit satisfaction	1.21 ***	1.16 – 1.27	1.18 ***	1.09 – 1.28	1.21 ***	1.14 – 1.29	1.20 ***	1.09 – 1.33
Essential service	1.28 ***	1.19 – 1.38	1.33 ***	1.18 – 1.50	1.27 ***	1.14 – 1.42	1.25 **	1.05 – 1.49
Suitable to reach desired destinations	1.62 ***	1.55 – 1.70	1.71 ***	1.57 – 1.87	1.63 ***	1.53 – 1.74	1.57 ***	1.42 – 1.74
Service is improving	1.29 ***	1.20 – 1.39	1.29 ***	1.13 – 1.47	1.34 ***	1.21 – 1.49	1.07	0.89 – 1.27
Support for funding	1.35 ***	1.21 – 1.50	1.41 ***	1.17 – 1.69	1.37 ***	1.17 – 1.60	1.42 *	1.08 – 1.86
Transit usage								
<i>Ref: Usage in the past week</i>								
Used in the past year	0.56 ***	0.47 – 0.66	0.61 ***	0.45 – 0.81	0.51 ***	0.39 – 0.66	0.52 **	0.35 – 0.76
Non-user	0.05 ***	0.04 – 0.06	0.05 ***	0.04 – 0.08	0.05 ***	0.04 – 0.07	0.06 ***	0.04 – 0.10
Proximity to rapid transit								
Metro [<600 m]	2.39 ***	1.49 – 3.95	2.30 ***	1.43 – 3.83				
LRT [<400 m]	1.31	0.84 – 2.06	0.92	0.53 – 1.64	2.45 *	1.18 – 5.38		
Reasonable travel time by transit								
<i>Ref: >65 min</i>								
≤15 min	1.39 **	1.11 – 1.76	1.77 **	1.20 – 2.61	1.36	0.98 – 1.91	0.88	0.50 – 1.59
20 - 35 min	1.59 ***	1.27 – 2.00	2.01 ***	1.37 – 2.94	1.51 *	1.09 – 2.09	1.15	0.67 – 2.01
40 - 60 min	1.41 **	1.10 – 1.82	1.74 *	1.12 – 2.70	1.39	0.97 – 2.01	0.89	0.49 – 1.65
Travel behavior								
Owns a bicycle	1.21 ***	1.09 – 1.34	1.30 **	1.07 – 1.56	1.24 **	1.07 – 1.44	1.21	0.95 – 1.53
Driving share [Past 7 days]	0.49 ***	0.40 – 0.62	0.78	0.52 – 1.17	0.41 ***	0.30 – 0.56	0.40 ***	0.24 – 0.66
Residential self-selection								
Being near transit	1.29 ***	1.23 – 1.35	1.24 ***	1.14 – 1.36	1.31 ***	1.22 – 1.41	1.36 ***	1.21 – 1.53
Being near cycling infrastructure	0.95 *	0.90 – 0.99	0.93	0.85 – 1.02	0.91 **	0.85 – 0.98	1.15 *	1.03 – 1.29
Socio-demographic								
Age	1.00	0.99 – 1.00	1.00	0.99 – 1.01	1.00	0.99 – 1.00	1.00	0.99 – 1.00
Gender [Ref: Men]								
Women	0.85 **	0.77 – 0.95	0.77 **	0.63 – 0.93	0.90	0.78 – 1.03	0.96	0.76 – 1.21
Household size [Ref: Five or more]								
One individual	1.55 ***	1.26 – 1.90	2.64 ***	1.86 – 3.73	1.09	0.80 – 1.48	0.97	0.58 – 1.62
Two to Four	1.39 ***	1.16 – 1.67	1.93 ***	1.44 – 2.58	1.20	0.92 – 1.57	0.71	0.45 – 1.12
Household income [Below 90k]	0.94	0.85 – 1.04	0.92	0.76 – 1.12	0.93	0.80 – 1.09	1.07	0.84 – 1.36
Immigrant	1.18 **	1.05 – 1.33	1.03	0.84 – 1.26	1.41 ***	1.18 – 1.67	0.94	0.70 – 1.25
Employment								
Worker	0.94	0.83 – 1.07	1.04	0.82 – 1.33	0.88	0.72 – 1.06	1.01	0.75 – 1.36
Student	0.87	0.70 – 1.07	0.63 *	0.43 – 0.94	1.03	0.75 – 1.43	1.02	0.66 – 1.60
Telecommuting frequency	1.02	0.99 – 1.05	1.03	0.97 – 1.08	1.01	0.97 – 1.05	1.01	0.94 – 1.08
Local urban environment								
Walk Score® [Ref: Car-dependent, 0–49]								
Somewhat walkable (50 - 69)	1.06	0.93 – 1.20	1.21	0.95 – 1.56	1.02	0.85 – 1.21	1.08	0.81 – 1.46
Walkable (70 - 100)	0.90	0.80 – 1.01	1.02	0.82 – 1.28	0.88	0.75 – 1.05	0.82	0.63 – 1.08
Region								
<i>Ref: Large CMAs (2M+)</i>								
Mid-sized CMAs (500k–1.5M)	0.59 ***	0.53 – 0.66						
Small CMAs (<500k)	0.44 ***	0.38 – 0.51						
<i>Ref: Vancouver</i>								
Toronto			0.83	0.66 – 1.04				
Montreal			0.85	0.68 – 1.07				
<i>Ref: Hamilton</i>								
Calgary					1.26	0.97 – 1.63		
Ottawa-Gatineau					0.86	0.68 – 1.11		
Edmonton					1.04	0.81 – 1.34		
Québec					1.10	0.85 – 1.43		
Winnipeg					0.59 ***	0.46 – 0.77		
<i>Ref: Victoria</i>								
Halifax							0.53 ***	0.39 – 0.73
Saskatoon							1.01	0.77 – 1.32
Observations	16,955		6,020		7,954		2,981	
R ² Tjur	0.602		0.519		0.601		0.594	

OR: Odds Ratio, CI: 95% Confidence Interval, *p < 0.05 **p < 0.01 ***p < 0.001.

Consistent with this, a robustness check estimating separate national models for users and non-users yielded broadly similar signs for key correlates, although magnitudes of effect differed between users and non-users (Appendix: Table A2). For example, perceived suitability (i.e., perceived accessibility) is strongly positive among both users and non-users, while driving share remains negatively associated with

intention in both groups. This suggests that, although retention and adoption intentions differ in their overall likelihood, both are associated with individual evaluations of whether transit is useful, attractive, and compatible with everyday travel needs.

In addition, driving behavior is also consistently associated with lower intention to use transit. In the national model, a higher share of

car trips over the past seven days is linked to substantially lower odds of intending to use transit (OR = 0.49, 95% CI 0.40–0.62), with similar or stronger effects in mid-sized and small CMAs (OR = 0.41 and 0.40, respectively). These findings echo socio-psychological work showing that stable, repeated behaviors, such as car use, can weaken the development of behavioral intentions, thereby inhibiting the formation of new transit-oriented behaviors (Chen and Chao, 2011). The fact that the negative association between driving and transit intention is strongest outside the largest CMAs suggests that breaking car habit may be particularly challenging in mid-sized and small metropolitan areas, where car dependence tends to be higher and transit networks less dense.

4.2.2. Perceptions of transit

Perceptions of transit emerge as strong correlates of intention, in line with the theory of planned behavior's emphasis on attitudinal evaluations as key drivers of behavioral intentions (Ajzen, 1991, 2011). Across all four models, higher overall satisfaction with transit services is associated with greater odds of intending to use transit (national OR = 1.21, 95% CI 1.16–1.27), with similar effects in each CMA size group. Among current transit users, this finding is consistent with transit loyalty studies showing that satisfaction is closely linked to reuse intentions (Carvalho et al., 2022; Van Lierop et al., 2018). Across the full sample, the positive association between satisfaction and future transit intention further suggests that improving transit experiences may matter both for retaining existing users and for encouraging future use among non-users, a pattern also observed in the separate user and non-user national models (OR = 1.26 and 1.11, respectively as shown in Appendix: Table A2).

Perceived accessibility, captured by whether respondents consider transit suitable for reaching their desired destinations, is one of the strongest attitudinal factors in the models. A one-point increase on this scale is associated with roughly 60–70% higher odds of intending to use transit (national OR = 1.62, 95% CI 1.55–1.70), with similarly large effects in all CMA size groups and a slightly stronger association in large CMAs (OR = 1.71). In this context, this measure can be interpreted as conceptually related, though not identical, to socio-psychological constructs such as perceived behavioral control and self-efficacy (Ajzen, 1991; Bandura, 1977), in that it reflects the extent to which individuals feel that transit offers a feasible way to access the activities they value, which in turn may shape their intentions to use transit. These findings expand earlier work linking perceived accessibility to observed transit mode share (Negm and El-Geneidy, 2025) by showing that it is also strongly associated with future intentions.

Normative and evaluative beliefs about transit also matter. Believing that transit is an essential service is positively associated with intention in all models (national OR = 1.28, 95% CI 1.19–1.38), suggesting that seeing transit as socially significant supports individual willingness to use it. Likewise, perceiving that service has improved over the past 12 months increases the odds of intending to use transit in the national, large-CMA, and mid-sized-CMA models (OR \approx 1.29–1.34), aligning with prior evidence that perceived service quality has a positive influence on behavioral intentions (De Oña, 2021; Fu et al., 2018; Nguyen-Phuoc et al., 2021). Finally, support for increasing operating funding is strongly and positively associated with intention across all models (OR \approx 1.35–1.42), suggesting that respondents who endorse additional funding for transit operations are also more likely to plan to use it themselves. In sum, these results indicate that intention to use transit is sensitive to how people evaluate transit services, including whether they see it as satisfactory, suitable to their daily needs, essential to society, or worthy of additional funding. This pattern reinforces the view that policies aimed at retaining and increasing ridership hinge on shaping positive perceptions of transit (Donald et al., 2014), including its quality, usefulness, and social value.

4.2.3. Proximity to rapid transit and travel time

Several transit network design factors further shape intentions. Proximity to rapid transit is positively associated with intention in contexts where such services are present. Living within 600 m of a metro station roughly doubles the odds of intending to use transit in both the national model (OR = 2.39, 95% CI 1.49–3.95) and the large-CMA model (OR = 2.30, 95% CI 1.43–3.83). In mid-sized CMAs, where LRT plays a more central role, living within 400 m of an LRT station is similarly associated with higher intention (OR = 2.45, 95% CI 1.18–5.38). These effects echo the ridership literature that emphasizes the importance of service frequency and supply (Lyons et al., 2017; Redelmeier and El-Geneidy, 2024) and suggests that rapid transit investments can strengthen not only observed transit ridership but also people's plans to use the system, particularly when stations are located within walking distance of residential areas.

Tolerable travel time expectations are associated with intention to use transit, although the pattern varies across CMA sizes. Relative to respondents who consider trips longer than 65 min by transit acceptable, those who view 20–35 min as a reasonable door-to-door travel time have higher odds of intending to use transit in the national (OR = 1.59, 95% CI 1.27–2.00), large-CMA (OR = 2.01, 95% CI 1.37–2.94), and mid-sized-CMA models (OR = 1.51, 95% CI 1.09–2.09). In the national and large-CMA models, the \leq 15-min and 40–60-min categories are also positively associated with intention, although with somewhat smaller coefficients. By contrast, none of the travel-time categories are statistically significant in the small-CMA model. These results suggest that perceived reasonable travel time is more strongly associated with future transit intention in larger metropolitan contexts, with the strongest correlate in the 20–35-min range. This is broadly consistent with previous work on tolerable travel time thresholds in North America (Carvalho and El-Geneidy, 2025; Milakis et al., 2015; Milakis and van Wee, 2018). From a planning perspective, these findings underline the importance of designing networks and land-use patterns that keep most routine destinations within this perceived reasonable time threshold, particularly in large and mid-sized metropolitan areas, to sustain and grow future transit use.

4.2.4. Residential self-selection and the local built environment

Residential self-selection and active travel orientations also matter. Across all models, respondents who reported that being near transit was an important factor in choosing their current home are more likely to intend to use transit (OR \approx 1.24–1.36), consistent with prior literature on the influence of residential self-selection attitudes on travel behavior (Cao et al., 2009; Guan et al., 2020). By contrast, broader neighborhood walkability, as measured by Walk Score® categories, is not statistically significant in any model. This suggests that neighborhood walkability is not independently associated with future transit intention once transit-specific perceived accessibility and attitudes, travel behavior, and residential self-selection are taken into account.

The role of proximity to cycling infrastructure is more nuanced. Nationally and in mid-sized CMAs, respondents who prioritized being near bike facilities show slightly lower odds of intending to use transit (national OR = 0.95, 95% CI 0.90–0.99; mid-sized OR = 0.91, 95% CI 0.85–0.98), whereas in small CMAs the association is positive (OR = 1.15, 95% CI 1.03–1.29). These associations should be interpreted cautiously for mid-sized CMAs, where a robustness check suggests that the negative association is not uniform across individual regions. This heterogeneity likely reflects contextual differences in cycling networks and seasonality across mid-sized metropolitan areas. By contrast, bicycle ownership captures a different dimension of mobility orientation. It is positively associated with intention in the national, large-, and mid-sized-CMA models (OR = 1.21–1.30), while the association is not statistically significant in small CMAs. This finding may reflect a broader multimodal orientation and openness to using multiple sustainable modes, particularly in larger metropolitan contexts.

4.2.5. Employment characteristics

Employment characteristics show limited associations with intention once other factors are controlled. Worker status and telecommuting frequency are not statistically significant in any model (e.g., national model: worker status OR = 0.94, 95% CI 0.83–1.07; telecommuting OR = 1.02, 95% CI 0.99–1.05), suggesting that their associations with future intention may operate through other factors, although this should not be interpreted as evidence that telecommuting is unimportant for post-pandemic transit recovery. By contrast, students in large CMAs have significantly lower odds of intending to use transit once other factors are controlled (OR = 0.63, 95% CI 0.43–0.94), even though the majority are current users in our sample (89.8%). This association is not statistically significant in the national, mid-sized, or small-CMA models. This suggests that, at least in large metropolitan areas, retaining student riders may require specific strategies, as many appear uncertain about continuing to use transit in the near future.

4.2.6. Socio-demographic characteristics

Socio-demographic patterns add further nuance, with gender playing a salient role in the national and large-CMA models. In the national model, women have lower odds of intending to use transit than men (OR = 0.85, 95% CI 0.77–0.95), with a stronger negative association in large CMAs (OR = 0.77, 95% CI 0.63–0.93). At the same time, the interaction between gender and transit identity reveals that among self-identified transit users, women have higher odds than men of intending to use transit in the future (national interaction OR = 1.45, 95% CI 1.11–1.89; large-CMA interaction OR = 2.30, 95% CI 1.45–3.67). These results suggest that women who are not currently transit users are less likely than men to express intention to use transit, whereas among current users, women express stronger retention intentions. Descriptive statistics provide additional context for this interaction: women riders in the sample report higher satisfaction with transit services (64.0% versus 44.2% among men) and are more likely to disagree that crime (50.3% versus 42.5%) or harassment (50.5% versus 41.6%) are problems on transit. Although these differences are not tested as mediating factors here, they suggest that safety perceptions and service experience may be relevant pathways that future research should examine, alongside trip purpose and care-related travel responsibilities.

Household structure and migration status are also associated with intention. Compared with respondents in large households (five or more members), those living alone or in two-to four-person households have higher odds of intending to use transit in the national and large-CMA models (OR \approx 1.39–2.64). Immigrants are more likely than non-immigrants to intend to use transit nationally (OR = 1.18, 95% CI 1.05–1.33) and especially in mid-sized CMAs (OR = 1.41). By contrast, neither age nor household income is statistically significant in any model, suggesting limited independent associations with future transit intention once other factors are taken into account.

4.2.7. Regional variations

Urban scale remains an important correlate of intention even after controlling for socio-demographic characteristics, transit perceptions and self-selection, travel behavior, and the local environment. In the national model, respondents in mid-sized CMAs have 41% lower odds of intending to use transit than those in large CMAs (OR = 0.59, 95% CI 0.53–0.66), while respondents in small CMAs have 56% lower odds (OR = 0.44, 95% CI 0.38–0.51). These results suggest that city scale matters not as an isolated factor, but as a proxy for broader differences in the context within which transit operates and intentions are formed. This interpretation is also supported by the stratified models, which reveal several systematic differences across CMA sizes in the factors associated with future transit intention. In particular, perceived accessibility shows a stronger association in large CMAs, reasonable travel time is more strongly associated with intention in large and mid-sized CMAs than in small ones, and driving has a much stronger negative association with intention outside the largest metropolitan areas. These findings are

consistent with the broader ridership literature suggesting that urban scale captures differences in density, service structure, and car dependence (Cervero and Guerra, 2011; Taylor and Fink, 2013; Wu et al., 2019) that shape how viable transit is perceived to be for everyday travel. Overall, these results contribute to the literature by showing that urban scale matters not only because baseline intention differs across CMA sizes, but also because the relative salience of key correlates of intention varies across metropolitan contexts.

Using, within each size group, the CMA with the highest weighted share of intention as the reference category (Vancouver, Hamilton, and Victoria), we find that within mid-sized CMAs, Winnipeg stands out with significantly lower odds of intending to use transit compared with Hamilton (OR = 0.59, 95% CI 0.46–0.77), aligning with generally less favorable transit perceptions (e.g., lower willingness to recommend and lower perceived service improvement). In the small-CMA group, Saskatoon shows significantly lower odds of intention relative to Victoria (OR = 0.53, 95% CI 0.39–0.73), whereas Halifax is statistically similar to Victoria. Notably, Saskatoon exhibits the highest average driving share (82.8% of trips by car, compared with 71.5% in Victoria and 76.7% in Halifax). Given Saskatoon's smaller sample size, excluding this CMA yields broadly similar coefficients and model fit, suggesting that the small-CMA model results are not unduly driven by that city. No significant differences in intention are found among the three largest CMAs (Toronto, Montreal, Vancouver).

4.3. Policy implications

The results highlight a set of factors that are consistently associated with higher intention to use public transit across Canadian CMAs, as well as some factors that differ by urban scale. In this section, we explore policy implications, focusing on system-wide priorities and noting where recommendations should be tailored for large, mid-sized, or small metropolitan areas. Table 4 provides a summary of main findings and policy recommendations.

First, future intentions to use transit are strongly associated with recent transit use and transit identity: self-identified transit users have much higher odds of intending to use transit in the next year, while non-users show low intention even after controlling for attitudes, behavior, and socio-demographics. From a policy perspective, this suggests agencies should treat ridership retention as at least as important as ridership growth, given the lower baseline intention among non-users. For current users, the findings are best interpreted in terms of retention intentions, implying that agencies should prioritize reliable, frequent service and consistently positive experiences, which prior research has linked to satisfaction, loyalty, and ridership. For non-users, by contrast, the results are better understood as reflecting openness to adoption, underscoring the need for strategies that make transit appear both viable and attractive for future use. The retention pattern is especially pronounced in mid-sized and small CMAs, where self-identified transit users exhibit higher odds of intending to keep using transit than in the national and large CMAs. In these more car-dependent settings, losing an existing rider may be particularly consequential, making retention strategies critical to sustaining and eventually growing ridership.

Our results also show that how people feel about transit, particularly their overall satisfaction and sense that service is improving, is linked to whether they intend to use it in the near future. From a policy perspective, this suggests that agencies should treat user experience as a core ridership strategy. This implies reducing critical negative incidents (Allen et al., 2019), which tend to leave stronger and more durable impressions than everyday positive experiences (Charpentier et al., 2016; Kahneman, 2011). The need to prioritize user experience is particularly important in mid-sized and small CMAs, where baseline satisfaction levels are lower. Notably, the user/non-user robustness check indicates that overall satisfaction is also positively associated with intention among non-users, suggesting that improving experiences may

Table 4
Summary of main findings and policy implications.

Theme	Main Finding	Policy Implication
<i>Transit identity & current use</i>	Transit identity and recent use strongly associated with higher intention; non-users have low intention.	Prioritize retention of current riders, especially in mid- and small CMAs where effects are stronger.
<i>Satisfaction</i>	Higher satisfaction and perceived improvement consistently boost intention.	Make user experience a core strategy.
<i>Essential service & support for funding</i>	Seeing transit as essential and supporting more funding raise intention.	Pair investments with clear communication on benefits and funding-use to sustain public and political support.
<i>Perceived accessibility</i>	Feeling that transit can reach desired destinations is strongly associated with intention.	Plan and market transit networks using accessibility metrics.
<i>Travel time & rapid transit</i>	Intention is highest when 20–35-min door-to-door times are seen as reasonable; living near metro/LRT raises intention.	Design networks around 20–35-min trips via rapid, direct, well-connected corridors.
<i>Car use and habit</i>	High recent driving and non-user status are strongly linked to low transit intention.	Combine service improvements with parking policy, traffic calming, and trial-pass programs, especially in mid- and small CMAs.
<i>Residential self-selection: near transit</i>	Valuing “being near transit” when choosing a home is tied to higher intention.	Expand housing options near transit hubs.
<i>Residential self-selection: near cycling infrastructure</i>	Cycling-related associations with transit intention vary by CMA context; bicycle ownership is generally positively associated with intention.	Integrate cycling and transit as complementary parts of a multimodal system (first/last mile access), tailored to local context.
<i>Gender</i>	Women overall have slightly lower intention, but women users show stronger future usage intentions than male users.	Improve and communicate safety to attract women non-users, and maintain high service quality to retain women users, especially in large CMAs.
<i>Immigrants</i>	Immigrants show higher intention nationally, especially in mid-sized CMAs.	Protect service quality and affordability in immigrant-rich areas as both equity and ridership strategies.
<i>Household structure</i>	Smaller households are more likely to intend to use transit than large households.	Make transit more family-friendly (fares, off-peak service), especially in large CMAs.
<i>Students</i>	In large CMAs, students intend less to keep using transit.	Target students in large CMAs with fare programs and service levels that encourage long-term retention.
<i>Urban scale</i>	After all controls, intention is still lower in mid- and small CMAs than in large CMAs.	Strengthen networks and transit-competitiveness in relation to car travel in mid- and small CMAs.

support both retention and openness to future use.

Perceptions that transit is an essential service and that increased operating funding is justified are also positively associated with intention. From a policy perspective, this highlights that operational and infrastructure improvements should be paired with clear communication. Transit agencies should explicitly link new investments and operational improvements to concrete benefits for riders (e.g., travel time savings) and be transparent about how funding translates into service. Strengthening the narrative of transit as essential infrastructure can help maintain public and political support for the operating resources needed to deliver the level of service required for ridership growth.

The models show that perceived accessibility (i.e., whether people feel transit is suitable for reaching their desired destinations) is a strong

factor associated with intention. Policy-wise, this suggests that agencies should not only expand service but also plan and communicate it in terms of what destinations become reachable. Accessibility metrics should be used both to guide network design (e.g., prioritizing corridors that unlock large gains in reachable opportunities) and to structure public communication (e.g., “increase in jobs within 30 min by transit”), making the benefits of investments more tangible.

Expectations about travel time also matter. Respondents who view a 20–35-min door-to-door transit trip as reasonable are more likely to intend to use transit than those who consider longer trips acceptable, pointing to a target range for everyday journeys and to the need to prioritize rapid transit network expansion, to provide direct routes on key corridors, to minimize unnecessary transfers, and to deploy limited-stop or express services. The proximity-to-rapid transit findings reinforce these implications, as living within walking distance of metro or LRT stations is often associated with much higher odds of intending to use transit in the contexts where these services operate.

Higher recent car use is strongly and negatively associated with intention to use transit, particularly outside the largest CMAs, and non-users across all CMA sizes have very low odds of planning to use transit in the near future. This pattern is consistent with socio-psychological work on habit, which suggests that established, repeated behaviors, such as car use, can block the formation of new behavioral intentions. From a policy perspective, this implies that service improvements alone are unlikely to shift entrenched drivers, especially in mid-sized and small CMAs where driving shares are highest and networks are less dense. Instead, transit investments need to be coupled with demand-management and “habit-breaking” measures (Eriksson et al., 2008; Fujii and Kitamura, 2003; Möser and Bamberg, 2008), such as parking pricing and supply management, car-restricted or traffic-calmed areas, employer- or campus-based transit benefits, and free or discounted trial passes, that lower the relative attractiveness of driving at key times and create openings for people to try transit.

The consistent association between “being near transit” as a home-location factor and intention to use transit suggests that pro-transit households who are able to locate near good service are more likely to plan to use it. This underscores the importance of land-use policies that expand housing opportunities in transit-oriented areas. The association is stronger outside large CMAs, particularly in small CMAs, indicating that enabling people to live in transit-supportive locations is a relevant strategy well beyond the biggest cities.

Cycling-related measures highlight the need to align active transportation investments with transit network design. Self-selection toward being near cycling infrastructure is associated with transit intention differently across CMA sizes, and in mid-sized CMAs this association varies across regions, as indicated by a robustness check. At the same time, bicycle ownership is positively associated with intention in the national, large-, and mid-sized-CMA models, suggesting that cycling may often reflect a broader multimodal orientation and openness to using multiple sustainable modes. In practice, agencies should design bike-sharing programs and bike networks as feeders and allies to transit. For instance, through secure parking at stations, safe and direct bike routes to rapid transit corridors, and integrated wayfinding and branding.

Although the weighted socio-demographic profiles are broadly similar across CMA sizes, the models show that some groups are systematically more or less likely to intend to use transit, and this varies by urban scale. Nationally and in large CMAs, women have slightly lower odds of intending to use transit than men, but the interaction with transit identity indicates that women who already see themselves as transit users are more likely than male users to plan to keep using transit. Policy-wise, this points to two complementary priorities: across CMAs, communicate and deliver improvements in safety and security to attract women who are not yet users, since descriptive patterns indicate less favorable safety and harassment perceptions among women non-users; and in large CMAs, sustain service quality to support retention among

existing women users.

Immigrants show higher intention to use transit nationally and especially in mid-sized CMAs. This suggests that maintaining good service quality and affordable fares in immigrant-rich neighborhoods, particularly in mid-sized cities, is both an equity and a ridership strategy. Household structure also matters compared with large (5+ person) households, one-person and 2–4-person households are more likely to intend to use transit, especially in large CMAs. Making transit more practical for families (e.g., family passes, stroller-friendly vehicles, reliable off-peak service) can help narrow this gap. Finally, in large CMAs, students have lower intention once other factors are accounted for, despite being frequent current users. This indicates a risk of losing them as they transition into new life stages, underscoring the value of strategies designed to retain them as long-term riders.

In sum, our findings suggest that broadly similar factors are associated with intention to use transit across Canadian CMAs, including transit identity, perceptions and experiences, car habit, and residential context. However, the strength of these associations varies with urban scale. Large CMAs benefit from higher baseline intentions and stronger rapid transit infrastructure, while mid-sized and small CMAs face greater structural and behavioral barriers. From a policy perspective, supporting mid-sized and smaller CMAs therefore requires both strengthening transit networks and pairing improvements with measures that reduce auto dependence and make transit a more viable option for everyday travel.

5. Conclusion

In this paper, we examine the determinants of intention to use public transit in the near future in Canada and assess how the significance of these correlates varies across metropolitan areas of different sizes. We estimate four weighted binary logistic regression models (a national model and three CMA-size specific models) that incorporate attitudinal and satisfaction measures, indicators of transit identity and current usage, proximity to rapid transit, perceived accessibility, tolerable travel time, residential self-selection, and socio-demographic characteristics. Drawing on a sample of 16,955 respondents from 12 Canadian CMAs, including both current users and non-users, we provide comparative evidence on the drivers of intention to use transit and highlight policy strategies that may need to be tailored to different urban scales.

Overall, the results suggest that broadly similar factors are associated with intention to use public transit across Canadian CMAs. Intention is strongly associated with current usage and identity as a transit user, with self-identified users far more likely to plan to use transit in the near future than non-users; in this sense, the findings reflect retention-oriented intention among current users and openness to adoption among non-users. Beyond this, several perception- and context-based factors consistently emerge as important factors, including higher satisfaction with transit, perceiving that service is improving, and seeing transit as suitable for reaching desired destinations. Access-related factors also matter, with proximity to rapid transit and reasonable travel-time expectations showing stronger associations in larger metropolitan contexts. Residential self-selection toward living near transit is also positively associated with intention across all CMA size groups. These factors are present across urban scales, although the strength of associations varies by CMA size, and socio-demographic associations (e.g., gender, immigrant status, household structure) vary across metropolitan contexts.

These findings carry several implications for policy. First, because intention is strongly associated with recent transit use and user identity, agencies should treat retention as a core objective alongside ridership growth, prioritizing reliable, frequent service and consistently positive experiences. Second, the central role of satisfaction, perceived

improvement, and perceived accessibility underscores the value of linking service changes to access improvements and concrete benefits for riders. Third, travel-time expectations, especially the salience of a 20–35-min “reasonable” door-to-door trip, and proximity to rapid transit are associated with higher intention, particularly in larger metropolitan contexts. This points to the value of prioritizing direct, well-connected rapid transit corridors and integrating land-use plans to expand housing opportunities near high-quality service. Finally, the negative association between car use and transit intention suggests that service improvements alone may be insufficient to shift entrenched drivers, reinforcing the role of complementary measures that reduce auto dependence, especially in mid-sized and small CMAs where car dependence is highest.

Even so, this work has limitations that should be acknowledged. First, the measure of intention is based on a single item that was recoded from a four-point Likert scale into a binary outcome, which improves interpretability but compresses variation and may mask more nuanced response patterns. To assess robustness, we estimated ordered specifications and found similar patterns to the binary models. Moreover, the dependent variable captures self-reported future intention rather than observed subsequent behavior. As a result, the findings should not be interpreted as evidence of realized behavioral change, particularly among non-users, for whom stated intention may reflect openness to adoption without necessarily translating into actual mode switching. Second, although the sample was carefully weighted to match CMA-level census distributions of age, gender, income, and commute mode, it is not a fully random sample of the population, and some groups may remain under- or overrepresented. Finally, because intention is measured for both current users and non-users, it captures both retention-oriented and adoption-oriented intentions; future work could examine these processes more directly by measuring mode switching and persistence. Future research could build on this research by exploring how intentions evolve over time and by linking changes in intention to subsequent shifts in travel behavior and to specific policy or investment decisions.

CRediT authorship contribution statement

Thiago Carvalho: 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, Investigation, Funding acquisition, Formal analysis, Data curation.

Conflicts of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Appendix

Appendix: Table A1: Ordered probit models

Variables	National		Large CMA		Mid-sized CMA		Small CMA	
	β	CI	β	CI	β	CI	β	CI
Thresholds								
Strongly disagree Disagree	-1.67 ***	-1.84 to -1.50	-1.37 ***	-1.66 to -1.08	-1.36 ***	-1.62 to -1.10	-2.09 ***	-2.50 to -1.68
Disagree Agree	-0.48 ***	-0.65 to -0.31	-0.37 *	-0.65 to -0.08	-0.13	-0.39 to -0.13	-0.70 ***	-1.10 to -0.29
Agree Strongly agree	1.12 ***	0.95 to 1.29	1.35 ***	1.06 to 1.64	1.44 ***	1.18 to 1.70	0.90 ***	0.49 to 1.30
Transit identity								
Transit user	0.61 ***	0.54 to 0.68	0.51 ***	0.39 to 0.62	0.68 ***	0.57 to 0.78	0.76 ***	0.59 to 0.94
Transit user vs Gender [Women]	0.06	-0.02 to 0.13	0.15 *	0.03 to 0.28	-0.01	-0.13 to 0.11	-0.01	-0.21 to 0.19
Transit satisfaction and perceptions								
Transit satisfaction	0.10 ***	0.09 to 0.12	0.10 ***	0.07 to 0.13	0.09 ***	0.06 to 0.11	0.15 ***	0.11 to 0.19
Essential service	0.22 ***	0.19 to 0.25	0.29 ***	0.24 to 0.34	0.21 ***	0.17 to 0.25	0.14 ***	0.08 to 0.20
Suitable to reach desired destinations	0.27 ***	0.25 to 0.29	0.28 ***	0.25 to 0.31	0.27 ***	0.25 to 0.30	0.27 ***	0.22 to 0.31
Service is improving	0.08 ***	0.06 to 0.11	0.04	-0.00 to 0.09	0.13 ***	0.09 to 0.17	0.01	-0.06 to 0.09
Support for funding	0.18 ***	0.14 to 0.22	0.17 ***	0.10 to 0.24	0.20 ***	0.14 to 0.27	0.20 ***	0.10 to 0.30
Transit usage								
<i>Ref: Usage in the past week</i>								
Used in the past year	-0.28 ***	-0.34 to -0.22	-0.15 ***	-0.24 to -0.06	-0.40 ***	-0.50 to -0.31	-0.31 ***	-0.46 to -0.16
Non-user	-1.37 ***	-1.44 to -1.29	-1.25 ***	-1.38 to -1.13	-1.50 ***	-1.61 to -1.39	-1.20 ***	-1.38 to -1.02
Proximity to rapid transit								
Metro [<600 m]	0.09	-0.03 to 0.21	0.13 *	0.01 to 0.25				
LRT [<400 m]	0.13	-0.00 to 0.27	0.09	-0.08 to 0.26	0.26 *	0.01 to 0.52		
Reasonable travel time by transit								
<i>Ref: >65 min</i>								
≤ 15 min	0.20 ***	0.11 to 0.28	0.26 ***	0.11 to 0.41	0.22 ***	0.09 to 0.34	0.06	-0.13 to 0.26
20 - 35 min	0.27 ***	0.18 to 0.35	0.30 ***	0.15 to 0.44	0.31 ***	0.19 to 0.42	0.13	-0.06 to 0.32
40 - 60 min	0.21 ***	0.11 to 0.30	0.21 *	0.04 to 0.37	0.27 ***	0.13 to 0.40	0.06	-0.15 to 0.28
Travel behavior								
Owens a bicycle	0.12 ***	0.08 to 0.16	0.16 ***	0.09 to 0.22	0.13 ***	0.07 to 0.19	0.07	-0.02 to 0.16
Driving share [Past 7 days]	-0.40 ***	-0.47 to -0.32	-0.32 ***	-0.44 to -0.19	-0.46 ***	-0.58 to -0.35	-0.48 ***	-0.66 to -0.29
Residential self-selection								
Being near transit	0.14 ***	0.12 to 0.16	0.15 ***	0.11 to 0.18	0.13 ***	0.10 to 0.15	0.18 ***	0.13 to 0.22
Being near cycling infrastructure	-0.01	-0.03 to 0.01	-0.05 **	-0.08 to -0.01	0.00	-0.02 to 0.03	0.06 **	0.02 to 0.11
Socio-demographic								
Age	0.00	-0.00 to 0.00	-0.00 *	-0.01 to 0.00	0.00	-0.00 to 0.00	0.00	-0.01 to 0.00
Gender [Ref: Men]								
Women	-0.07 **	-0.11 to -0.02	-0.13 **	-0.21 to -0.05	-0.04	-0.10 to 0.02	0.00	-0.10 to 0.10
Household size [Ref: Five or more]								
One individual	0.22 ***	0.14 to 0.30	0.40 ***	0.26 to 0.53	0.08	-0.04 to 0.20	0.11	-0.09 to 0.31
Two to Four	0.16 ***	0.09 to 0.23	0.27 ***	0.16 to 0.39	0.12 *	0.01 to 0.22	-0.05	-0.23 to 0.13
Household income [Below 90k]	-0.07 ***	-0.11 to -0.03	-0.10 **	-0.17 to -0.03	-0.05	-0.11 to 0.01	-0.03	-0.13 to 0.06
Immigrant	0.09 ***	0.05 to 0.13	0.03	-0.04 to 0.10	0.14 ***	0.07 to 0.21	0.08	-0.03 to 0.19
Employment								
Worker	-0.04	-0.09 to 0.01	-0.02	-0.11 to 0.07	-0.06	-0.13 to 0.02	-0.02	-0.14 to 0.09
Student	0.01	-0.06 to 0.09	-0.03	-0.16 to 0.11	0.06	-0.06 to 0.17	-0.03	-0.20 to 0.15
Telecommuting frequency	0.01	-0.00 to 0.02	0.01	-0.01 to 0.03	0.01	-0.01 to 0.03	-0.01	-0.03 to 0.02
Local urban environment								
Walk Score® [Ref: Car-dependent, 0-49]								
Somewhat walkable (50 - 69)	0	-0.05 to 0.05	-0.01	-0.10 to 0.09	-0.01	-0.08 to 0.06	0	-0.11 to 0.12
Walkable (70 - 100)	-0.05 *	-0.10 to -0.01	-0.08	-0.16 to 0.01	-0.04	-0.11 to 0.02	-0.06	-0.16 to 0.05
Region								
<i>Ref: Large CMAs (2M+)</i>								
Mid-sized CMAs (500k-1.5M)	-0.20 ***	-0.25 to -0.16						
Small CMAs (<500 k)	-0.28 ***	-0.33 to -0.22						
<i>Ref: Vancouver</i>								
Toronto			-0.04	-0.12 to 0.04				
Montreal			-0.11 **	-0.19 to -0.03				
<i>Ref: Hamilton</i>								
Calgary					0.20 ***	0.10 to 0.30		
Ottawa-Gatineau					0.27 ***	0.17 to 0.36		
Edmonton					0.22 ***	0.13 to 0.30		
Québec					0.19 ***	0.10 to 0.28		
Winnipeg					0.24 ***	0.14 to 0.34		
<i>Ref: Victoria</i>								
Halifax							-0.1	-0.21 to 0.00
Saskatoon							-0.24 ***	-0.35 to -0.13
Observations	16,955		6,020		7,954		2,981	
R ² Tjur	0.658		0.603		0.657		0.645	

β : Latent-scale coefficient, CI: 95% Confidence Interval, * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Appendix: **Table A2:** Binary logistic regression results (national level: user vs. non-user)

Variables	Transit User		Non-User	
	OR	CI	OR	CI
Intercept	6.93 ***	4.15 – 11.63	0.69	0.30 – 1.57
Transit satisfaction and perceptions				
Transit satisfaction	1.26 ***	1.20 – 1.33	1.10 *	1.02 – 1.19
Essential service	1.38 ***	1.27 – 1.51	1.14 *	1.01 – 1.29
Suitable to reach desired destinations	1.74 ***	1.65 – 1.84	1.65 ***	1.53 – 1.79
Service is improving	1.23 ***	1.14 – 1.32		
Support for funding	1.39 ***	1.23 – 1.58	1.31 **	1.07 – 1.60
Transit usage				
Ref: Usage in the past week				
Used in the past year	0.34 ***	0.29 – 0.40		
Proximity to rapid transit				
Metro [<600 m]	2.08 **	1.25 – 3.66	3.64 *	1.26 – 9.75
LRT [<400 m]	1.13	0.72 – 1.84	2.32	0.89 – 5.77
Reasonable travel time by transit				
Ref: >65 min				
≤15 min	1.46 **	1.09 – 1.94	1.35	0.91 – 2.05
20 - 35 min	1.51 **	1.15 – 1.99	1.84 **	1.26 – 2.78
40 - 60 min	1.39 *	1.02 – 1.88	1.54	0.99 – 2.45
Travel behavior				
Owns a bicycle	1.16 *	1.03 – 1.31	1.21	1.00 – 1.47
Driving share [Past 7 days]	0.41 ***	0.32 – 0.53	0.38 ***	0.25 – 0.57
Residential self-selection				
Being near transit	1.32 ***	1.25 – 1.40	1.36 ***	1.24 – 1.49
Being near cycling infrastructure	0.90 ***	0.85 – 0.96	1.10 *	1.00 – 1.20
Socio-demographic				
Age	1.00	0.99 – 1.00	0.99 *	0.99 – 1.00
Gender [Ref: Men]				
Women	0.92	0.82 – 1.03	0.85	0.71 – 1.01
Household size [Ref: Five or more]				
One individual	1.46 **	1.15 – 1.84	1.41	0.94 – 2.16
Two to Four	1.48 ***	1.21 – 1.80	1.08	0.75 – 1.59
Household income [Below 90k]	0.90	0.80 – 1.02	1.12	0.92 – 1.36
Immigrant	1.25 **	1.09 – 1.43	1.10	0.87 – 1.40
Employment				
Worker	0.99	0.85 – 1.16	0.72 **	0.56 – 0.92
Student	0.97	0.77 – 1.22	1.11	0.63 – 1.86
Telecommuting frequency	1.02	0.99 – 1.06	1.06 *	1.00 – 1.12
Local urban environment				
Walk Score® [Ref: Car-dependent, 0–49]				
Somewhat walkable (50 - 69)	1.15	0.99 – 1.34	0.89	0.71 – 1.12
Walkable (70 - 100)	1.00	0.87 – 1.15	0.73 **	0.59 – 0.91
Region				
Ref: Large CMAs (2M+)				
Mid-sized CMAs (500k–1.5M)	0.60 ***	0.53 – 0.69	0.56 ***	0.45 – 0.70
Small CMAs (<500k)	0.45 ***	0.38 – 0.53	0.44 ***	0.33 – 0.58
Observations	13,006		3,949	
R ² Tjur	0.299		0.139	

OR: Odds Ratio, CI: 95% Confidence Interval, *p < 0.05 **p < 0.01 ***p < 0.001.

Data availability

The data that has been used is confidential.

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