Transportation Research Part A 208 (2026) 104983

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Do intentions translate into use? Transit market evolution and intention-behavior gaps after a new BRT service in Montreal, Canada

Thiago Carvalho, Ahmed El-Geneidy *

School of Urban Planning, McGill University, Canada

ARTICLE INFO

Keywords:
Bus rapid transit
Market segmentation
Intention-behavior gap
Behavioral change
Ridership

ABSTRACT

This study investigates how transit market profiles evolve and how intentions align with actual behavior following the implementation of a Bus Rapid Transit (BRT) system in Montreal, Canada. While prior research has focused primarily on ridership trends, this paper adopts a behavioral lens, integrating market segmentation and the intention-behavior gap concept to examine individual-level behavior. Drawing on longitudinal data from the Montreal Mobility Survey, the analysis uses a pre-BRT sample of 578 respondents (2021) and a post-BRT sample of 1882 respondents (2023–2024), including a panel of 209 individuals who responded before and after implementation. Using exploratory factor analysis and weighted k-means clustering, four market profiles were identified both before and after implementation: transit-reliant riders, telecommuter choice riders, walkability-oriented individuals, and car-oriented individuals. While the profile structure was consistent at the aggregate level, panel tracking showed heterogeneous profile stability: car-oriented individuals were most likely to remain in their baseline profile, whereas telecommuter choice riders were most likely to transition to a different profile. A separate multinomial model assessed the intention-behavior gap, revealing that closeness to the infrastructure can influence intention follow-through. The results provide empirical evidence that infrastructure alone is insufficient to ensure adoption and suggest that targeted interventions are necessary to bridge the gap between intention and use. The findings in this study can be of interest to transit agencies and policymakers interested in user-centered public transit planning strategies.

1. Introduction

Designed to deliver high-capacity, rail-like service at a lower cost, Bus Rapid Transit (BRT) systems have been associated with travel time savings, reliability gains, and, in many cases, increased ridership (Currie and Delbosc, 2014; Deng and Nelson, 2011; Levinson et al., 2003). However, the extent to which these systems successfully attract and retain users depends not only on their technical and operational performance but also on users' perceptions, attitudes, and willingness to adopt the service (Cain and Flynn, 2013). Understanding how the public responds to these investments over time is crucial for ensuring the long-term success of such interventions.

While much of the research on BRT implementation has focused on operational outcomes and ridership forecasts (Oort and

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

https://doi.org/10.1016/j.tra.2026.104983
Received 23 May 2025; Received in revised form 11 March 2026; Accepted 15 March 2026
Available online 21 March 2026
0965-8564/

MennoYap, 2021), fewer studies have examined the evolution of the transit market in response to a new BRT infrastructure. By transit market, we mean the composition of traveler segments in a region, including who uses transit (or could use it) and the factors shaping usage. Even when individuals express positive attitudes or intentions towards a new service, actual adoption is not guaranteed (Chen and Chao, 2011; Sheppard et al., 2002; Thøgersen, 2006). This disconnect is well documented in the behavioral literature, which is known as the intention-behavior gap. In transportation research, this gap is particularly relevant when exploring the impact of new transit infrastructure, where adoption may be hindered by entrenched habits (Verplanken et al., 2002) or perceived inconveniences (Schwanen et al., 2012).

This study uses the intention-behavior gap concept to examine how the market evolved in response to the opening of a BRT system in Montreal, Canada. Drawing from a multi-year dataset collected before BRT implementation (N = 578) and from one to two years post-opening (N = 1882), factor-cluster analysis is employed to identify distinct market profiles based on respondent's intentions, attitudes, and behaviors. Then, two modeling strategies are employed to investigate the dynamics of market evolution using a weighted subset of panel respondents (N = 209). First, a binary logistic regression assesses the likelihood that individuals remain in the same cluster over time, offering insight into the consistency of the broader market profile structure, i.e., market stability, following major infrastructure investments. Second, a multinomial logistic regression analyzes the intention–behavior gap by modeling which user segments consistently used, abandoned, or unexpectedly adopted the new BRT service. Importantly, we do not attribute pre/post differences to intentions alone; profiles and transitions reflect joint changes across attitudinal, resource, and behavioral dimensions.

By integrating market segmentation with the intention-behavior gap concept and applying a longitudinal design, this study contributes to a deeper understanding of both the evolution of transit markets and the behavioral consistency of potential and non-potential users. In doing so, it provides empirical evidence on how exposure to new transit infrastructure shapes travel decisions, while highlighting behavioral dynamics that underline broader adoption patterns. These findings offer practical insights for improving ridership forecasting and evaluating the real-world performance of major transit interventions.

The remainder of the paper is structured as follows. Section 2 summarizes prior work on determinants of BRT ridership, market segmentation, and the intention-behavior gap in the context of new transit infrastructure. Section 3 introduces the case study and data sources. Section 4 details the methods used for the segmentation approach and the regression models. Finally, Section 5 reports and discusses the findings, and Sections 6–7 discuss policy implications and conclude.

2. Literature review

Understanding how individuals respond to new BRT infrastructure requires engaging with three interrelated strands of the transportation literature, the determinants of BRT ridership, the segmentation of transit markets, and the disconnect between intentions and behavior, all explored in this section.

2.1. BRT ridership and behavioral change

Research has shown that BRT corridors can serve as catalysts for behavioral change (Deng and Nelson, 2012; Levinson et al., 2003), encouraging modal shift away from private car use (Ernst, 2005; Levinson et al., 2003). For example, Ernst (2005) found that one month after the launch of the TransJakarta BRT system, 20% of users had previously completed the same trip using private motorized transport. Similarly, Stewart et al. (2017) provide causal evidence from King County, Washington, demonstrating that BRT implementation led to a 35% increase in ridership relative to conventional bus routes, and a 29% increase compared to express services. In analyzing the comparative appeal of different transit modes, Currie (2005) concluded that BRT systems, when offering comparable levels of service, can be just as effective as rail in attracting ridership.

Among the various service features influencing BRT ridership, service frequency consistently emerges as an essential factor (Cervero et al., 2010; Currie and Delbosc, 2011). Frequency is shaped by broader corridor design and operational characteristics. In a comparative study of 121 BRT systems across 12 countries, Hensher et al. (2014) found that higher service frequency was positively associated with population density, the presence of trunk lines, dedicated bus lanes, and overtaking lanes at critical points along the corridor. Beyond service features, BRT ridership is influenced by the surrounding land use, including the presence of mixed-use developments, pedestrian-friendly infrastructure, and nearby public facilities and services (Rodriguez and Vergel-Tovar, 2018; Vergel-Tovar and Rodriguez, 2018). Transit image, shaped by both service characteristics as well as intangible factors, such as comfort and safety, also contribute to the system's ridership attraction potential (Cain and Flynn, 2013).

Together, these findings highlight the multifaceted nature of ridership growth, shaped by operational design, urban form, and user perceptions. However, while this body of research provides valuable insights into the drivers of aggregate ridership trends, it often overlooks the heterogeneity of user responses and the attitudinal dynamics underlying individual decision-making. To better capture the nuance in behavioral responses, many researchers explore market segmentation techniques, which allow for the identification of distinct user profiles based on travel preferences, attitudes, and behavior (Anable, 2005; Diana and Mokhtarian, 2009).

2.2. Market segmentation in transportation research

One of the earliest and most enduring approaches to understanding transit user diversity is the distinction between captive and choice riders (Beimborn et al., 2003; Guerra, 2022; Wilson et al., 1984). Captive riders are typically dependent on public transit due to economic or physical constraints (Beimborn et al., 2003), whereas choice riders are those who opt for transit of their own volition (Guerra, 2022; Wilson et al., 1984) often due to convenience or personal values (Zhao et al., 2014). Building upon this framework, Van

Lierop and El-Geneidy (2017) identified a third market segment, captive-by-choice riders, individuals who have the means to travel by other modes but consciously choose transit for experiential or lifestyle-related reasons. This three-level classification was also observed post-pandemic by Carvalho and El-Geneidy (2024), who documented a transit market shrinkage shaped by increased telecommuting and reduced usage frequency.

While foundational, captive-choice typologies have been criticized for oversimplifying market complexity and reinforcing negative stereotypes. Other scholars have moved beyond this paradigm using data-driven techniques to more accurately capture the diversity of transit users. These approaches incorporate combinations of personal (Fu et al., 2018; Mugion et al., 2018; Tyrinopoulos and Antoniou, 2008; Vicente et al., 2020), attitudinal (Anable, 2005; Cheng et al., 2017; Eldeeb and Mohamed, 2020; Fu and Juan, 2017; Jamal et al., 2023; Kim and Ulfarsson, 2012; Krizek and El-Geneidy, 2007), behavioral (Allen et al., 2019; Shiftan et al., 2015; Sun and Duan, 2019; Viallard et al., 2019), and geographic variables (Chen, 2016; Grisé and El-Geneidy, 2018) to develop more nuanced market profiles. Across this body of work, attitudinal and behavioral measures are most frequently combined, whereas geographic indicators are less commonly incorporated and personal characteristics are often used for a priori subgroup comparisons (see Appendix A1 for a study-by-study summary).

Methodologically, many of these studies operationalize segmentation using factor analysis followed by cluster analysis (often k-means or hierarchical methods) (Alousi-Jones et al., 2025; Carvalho and El-Geneidy, 2024; Damant-Sirois et al., 2014; Dent et al., 2021). In addition to factor-cluster approaches, several studies apply latent-class methods (e.g., latent class analysis, latent class clustering, and latent class choice models) to represent unobserved heterogeneity and derive probabilistic segments from attitudes or choice trade-offs (Eldeeb and Mohamed, 2020; Jamal et al., 2023; Mesbah et al., 2022). Latent class choice models are particularly common when segmentation is inferred directly from observed or stated choices, whereas factor-cluster approaches remain widely used when segmentation is based on psychometric constructs derived from attitudinal indicators.

Despite advancing the understanding of user heterogeneity, most studies rely on cross-sectional data, offering a static view of user attitudes and behaviors at a given point in time. This limits their ability to capture how markets evolve over time, particularly in response to major interventions such as the introduction of new transit infrastructure. Some longitudinal studies have examined behavioral change following the introduction of new rapid transit infrastructure, including changes in mode choice and car use around the Porto metro system (Ibraeva et al., 2022, 2023). However, these studies do not examine the evolution of attitudinal-behavioral market profiles or whether stated pre-implementation intentions materialize into actual ridership once the infrastructure is in place. One exception is Dent et al. (2021), who used pre-launch data to identify intention-based user segments for Montreal's new LRT project, the Réseau Express Métropolitain (REM). However, that analysis also stops short of assessing whether those stated intentions translated into actual use after opening.

This gap is critical, as intentions do not always lead to behavior. As Anable (2005) argues, similar behaviors may arise from different motivations, and conversely, similar attitudes may produce divergent behavioral outcomes. To better understand these dynamics, researchers have turned to theories of behavioral consistency and intention-behavior alignment, offering a path to understand not only who is likely to adopt transit services, but also why they follow through (or fail to) on those intentions.

2.3. *The intention-behavior gap in the context of new transit infrastructure*

The disconnect between what people say they intend to do and what they actually do has long been a focus of behavioral research. In the transport field, this discrepancy, commonly referred to as the intention-behavior gap, is particularly relevant when evaluating the adoption of new transit infrastructure. The Theory of Planned Behavior (TPB) (Ajzen, 1985, 1991, 2011) has served as an important framework for understanding this gap. According to TPB, behavior is primarily guided by behavioral intentions, which in turn are shaped by attitudes, subjective norms, and perceived behavioral control. However, TPB acknowledges that the path from intention to action is not deterministic; intentions are necessary but not always sufficient to produce behavior. This is supported by empirical evidence, a *meta*-analysis by Sheppard et al. (2002) found intentions and behavior to be only moderately correlated ($r = 0.53$) suggesting that a substantial portion of behavioral variance remains unexplained by intention alone.

This gap can be attributed to a range of barriers to behavioral change. Although direct evidence on why individuals may fail to follow through on their intentions to adopt new transit infrastructure is limited, insights from the broader literature on mode switching and sustainable transport behaviors offer valuable guidance. Among the most significant barriers is habit (Friedrichsmeier et al., 2012; Verplanken et al., 2002). When a behavior becomes habitual, the decision-making process is no longer reasoned (Gärling and Garvill, 1993), and new and relevant information is often disregarded (Gärling and Axhausen, 2003). As a result, even favorable intentions may not translate into behavior without substantial contextual disruption (Fujii et al., 2001), including key life-course events (i.e., residential relocation, childbirth) and broader contextual changes/interventions (Müggenburg et al., 2015). Studies have shown that habit significantly impedes mode switching intentions (Chen and Chao, 2011; Thøgersen, 2006) while moderating the intention-behavior relationship (Gardner, 2009).

Closely related to habit, car ownership further constrains behavioral change by reinforcing routine car use and reducing the influence of positive attitudes toward alternative modes such as public transit (Bamberg and Schmidt, 2003; Schwanen et al., 2012; Thøgersen, 2006). Additional barriers include the lack of perceived viable alternatives, socio-economic constraints, and psychological factors such as inertia, uncertainty, and the effort required to modify established routines (Gärling and Schuitema, 2007; Nolte and Schaefer, 2024; Schwanen et al., 2012; Thøgersen, 2006).

Affordability constraints can constrain behavioral change, including through suppressed travel demand among low-income households or, particularly in car dependent contexts, through forced car ownership and car-related economic stress (Mattioli et al., 2017). In North America, Allen and Farber (2020b) show that low-income households increasingly concentrate in auto-oriented suburbs with lower transit service and walkability, facing greater barriers to daily travel and activity participation, especially when car access is unaffordable. Among transit users, fare costs can further constrain travel, with stronger impacts for disadvantaged populations (El-Geneidy et al., 2016). Finally, care responsibilities and household structure (e.g., the presence of children) can intensify time constraints and trip-chaining demands (often in gendered and income-stratified ways) making mode change harder in practice (McCarthy et al., 2017; Ravensbergen et al., 2023). Importantly, for new transit services, behavioral intentions are measured prior to implementation and, therefore, are based on expectations rather than lived experience. Accordingly, observed intention-behavior discrepancies may reflect not only behavioral and social barriers, but also uncertainty regarding service performance and practical fit to established routines.

In the specific case of new transit infrastructure, the intention-behavior gap poses important questions for both planning and evaluation, such as (i) how do individual-level intentions towards new services translate into behavior once the infrastructure becomes available? (ii) who adopts the service as expected and who does not? and (iii) what role does pre-existing market profiles play in shaping those outcomes? To answer these questions, this study integrates market segmentation and intention-behavior gap frameworks within a longitudinal evaluation of a newly implemented BRT system. By using factor and cluster analysis to define market segments and tracking individuals over time, the study explores both market stability and how stated intentions align (or fail to align) with revealed behavior. In doing so, this study moves beyond aggregate cross-sectional assessments of ridership, instead highlighting the behavioral dynamics that shape system adoption and long-term success.

3. Study context and data sources

3.1. Case study: The Pie-IX BRT (Montreal, Canada)

Located on the east side of Montreal, Canada, the Pie-IX BRT is a $523 million Canadian dollars project spanning thirteen kilometers with seventeen operational stations and three more under construction in the far south of the route. Running in a north–south direction along Pie-IX Boulevard, the corridor connects with multiple east–west commuter routes and forms part of the broader transit network operated by Société de Transport de Montreal (STM). The BRT line partially replaced service offered by route 139, which continues to operate in parallel to the corridor with reduced service frequency.

The Pie-IX BRT officially opened in November 2022 after a four-year construction period. In 2019 (pre-pandemic), route 139, which was the corridor's main bus service, carried about 29,500 weekday riders. Ridership fell markedly during COVID-19 to about 11,500 weekday riders in 2022 (prior to BRT operations). Following implementation, early-2023 data show that the BRT route carried around 30,000 weekday riders, while the local route 139 carried about 3000. These ridership figures indicate that the BRT primarily

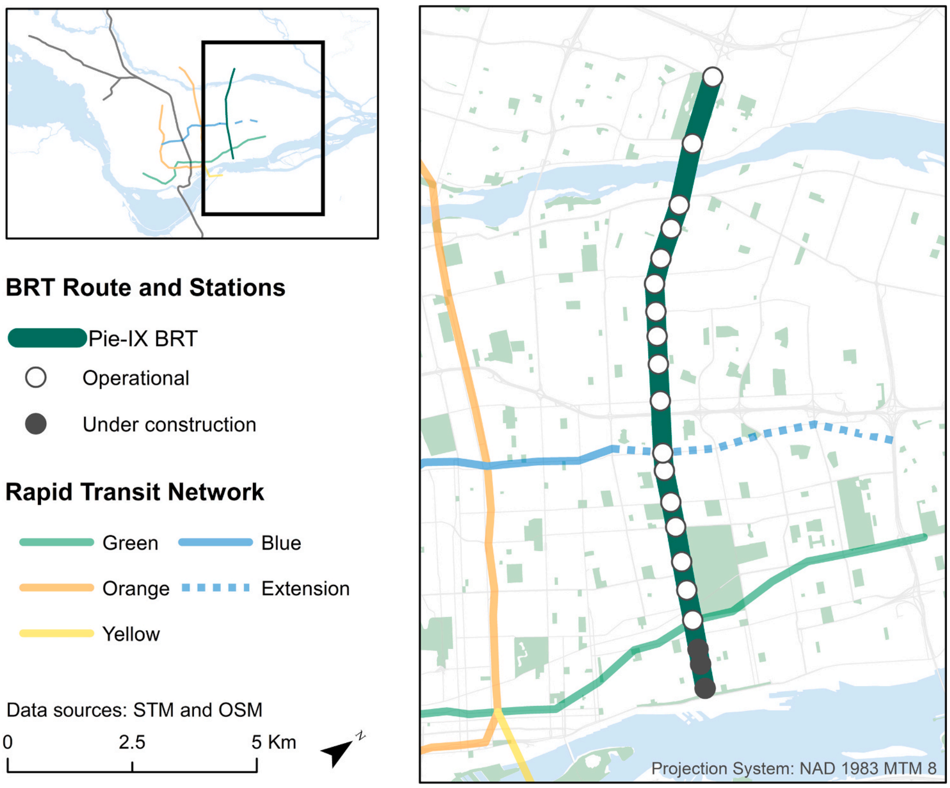

Fig. 1. The Pie-IX BRT corridor in the context of Montreal's rapid transit network.

restored corridor ridership to pre-pandemic levels. Overall, the corridor incorporates key design elements commonly associated with BRT systems worldwide, including center-running dedicated lanes, transit signal priority, all-door and platform-level boarding, and higher-capacity articulated buses. Fig. 1 is an illustration of the Pie-IX BRT corridor in the context of Montreal's rapid transit network.

Pie-IX Boulevard, where the corridor is located, is a major arterial that cuts across a range of neighborhoods on the eastern portion of the Island of Montreal. The corridor passes through areas with lower average household incomes, approximately 33% below the citywide average (StatCan, 2016), and higher concentrations of immigrants and visible minorities compared to Montreal as a whole (StatCan, 2021). While the corridor is not historically underserved by transit, it was selected for the BRT project based on its strong projected ridership and strategic location within the existing network.

3.2. Data source: The Montreal Mobility Survey (MMS)

This study draws on the Montreal Mobility Survey (MMS), a multi-wave, bilingual, online survey with both repeated cross-sectional samples and a longitudinal panel component administered by the Transportation Research at McGill (TRAM) group across the Greater Montreal region. The MMS is an extensive survey including over 100 questions related to perceptions and intentions toward new transit infrastructure (including the Pie-IX BRT), travel behavior (e.g., recent mode use and car access), and socio-demographic characteristics (e.g., age, gender, income, immigrant status). In this study, we focus on attitudinal/perception items, mobility resources and recent travel behavior measures, and Pie-IX BRT intention/usage indicators. Specific variables are introduced and defined as needed in the Methods section.

Across all waves, the MMS was administered in the Fall over approximately a month (with start dates between October and November, depending on the wave) among those aged 18 and over living in the Montreal metropolitan region. Multiple recruitment strategies were employed to build a large and diverse sample, including advertisements through a marketing company (Léger), targeted social media campaigns focused on the Montreal region, flyer distribution (in-person around Montreal and via mail), and an opt-in participant mailing list maintained by the research team, following best practices outlined by Dillman et al. (2014). Incentives were provided to encourage participation (e.g., entry into prize raffles), with cash incentives for panel respondents. All participants provided informed consent, and survey procedures were reviewed and approved by the appropriate institutional research ethics review process.

To ensure comparability and data quality, a consistent cleaning strategy was applied across waves. The exclusion criteria included a short completion time, incomplete responses, and multiple responses from the same email address or IP address. Responses were also excluded when geocoded locations were invalid, such as those who placed a pin representing their home, school, and/or work location outside of the Montreal metropolitan area or in water bodies. Further detail on the survey instrument and cleaning procedures is available in Victoriano-Habit et al. (2024), including wave-specific counts of observations dropped and retained at each cleaning step. The analyses in this study were conducted using the resulting cleaned MMS datasets.

3.3. Analytic sample and wave alignment

To analyze changes in the market profiles and examine the relationship between intention and subsequent behavior, we use both cross-sectional and panel data from the MMS. The 2021 wave of the MMS, conducted one year prior to the BRT's implementation, is used to characterize pre-implementation market profiles and intentions to use the Pie-IX BRT. Follow-up surveys in 2023 and 2024, conducted one and two years after the BRT opened, capture post-implementation patterns in user characteristics and travel behavior.

The analytic sample is restricted to respondents living along the Pie-IX BRT corridor and aware of the project. Restricting the analytic sample to respondents aware of the project helps ensure usage intention is reported with at least a basic understanding of the planned service. The corridor geography was defined using the BRT route from GTFS data and was constructed to encompass the full extent of the BRT path, accounting for the system's multiple trip patterns and time-of-day variations. Respondents were included if their geocoded home location fell within a 2.5 km Euclidean buffer of the corridor, intended to represent a multimodal access

Table 1
Unweighted sample composition across waves (comparability check for weighting dimensions).

Variable	2021 Wave	2023–2024 Waves	Panel baseline (2021)
N (analytic sample)	578	1882	209
Gender			
Men	67.6% (391)	44.1% (830)	67.0% (140)
Women	29.6% (171)	52.2% (983)	30.6% (64)
Non-binary	2.8% (16)	3.7% (69)	2.4% (5)
Age			
18–35	22.5% (130)	35.2% (643)	17.2% (36)
36–64	61.2% (354)	52.4% (958)	65.6% (137)
65 and over	16.3% (94)	12.4% (226)	17.2% (36)
Income [in CAD]			
Low income	36.5% (211)	31.9% (600)	30.6% (64)
Middle income	37.0% (214)	38.4% (722)	38.3% (80)
High income	26.5% (153)	29.8% (560)	31.1% (65)

Note: Weighting targets are limited to variables with corridor-level 2021 census benchmarks (age, gender, income).

catchment (walking at shorter distances, cycling, and connections via nearby public transit services).

Post-implementation data (2023–2024) were combined to increase statistical power while ensuring comparability across time. The combined dataset retained only items asked with identical wording and response scales in both years; wave-specific items were excluded from segmentation and modeling. The only planned difference between pre- and post-implementation measures is the BRT adoption indicator: intention to use the BRT is used prior to implementation, whereas BRT usage is used post-implementation.

In 2021, 578 survey respondents lived within the 2.5 km catchment area. In the combined 2023–2024 sample, the analytic sample was 1882; when respondents participated in both post-implementation waves, only their most recent response was retained (i.e., 2024 when available). A subset of 209 individuals participated both before and after the BRT opened and forms the longitudinal panel used to track individual-level transitions between market profiles (matched to the most recent post-implementation response). The longitudinal panel enables within-person comparisons; however, the sample size may limit statistical power for detecting smaller effects and interactions.

Table 1 reports the unweighted sample composition for the variables used in deriving survey weights (gender, age, and household income). Because sample composition differs across waves, all descriptive statistics and models in this study use weights to align each wave's corridor sample to the 2021 Census distribution on these dimensions. Table 1 is included only to document compositional differences that the weights are designed to correct; the weighting procedure is described in Section 4.2 for the cross-sectional samples and Section 4.3 for the panel sample.

Fig. 2 illustrates the geographic distribution of the respondents' home locations.

While the cross-sectional data enables analysis of broader shifts in user profiles over time, the panel data provides a unique opportunity to observe behavioral consistency and change over time on an individual basis, including whether intentions expressed prior to implementation aligned with actual BRT usage.

4. Methods

This section describes the multi-step analytical approach used to evaluate how transit market profiles evolved following the implementation of the Pie-IX BRT and to assess the intention-behavior relationship. The repeated cross-sectional data are used to identify and characterize market profiles before and after implementation, while the longitudinal panel is used to examine within-person profile retention and intention-behavior alignment over time. Specifically, we (i) estimate exploratory factor models separately for the pre-implementation (2021) and post-implementation (2023–2024) samples to derive latent constructs from shared

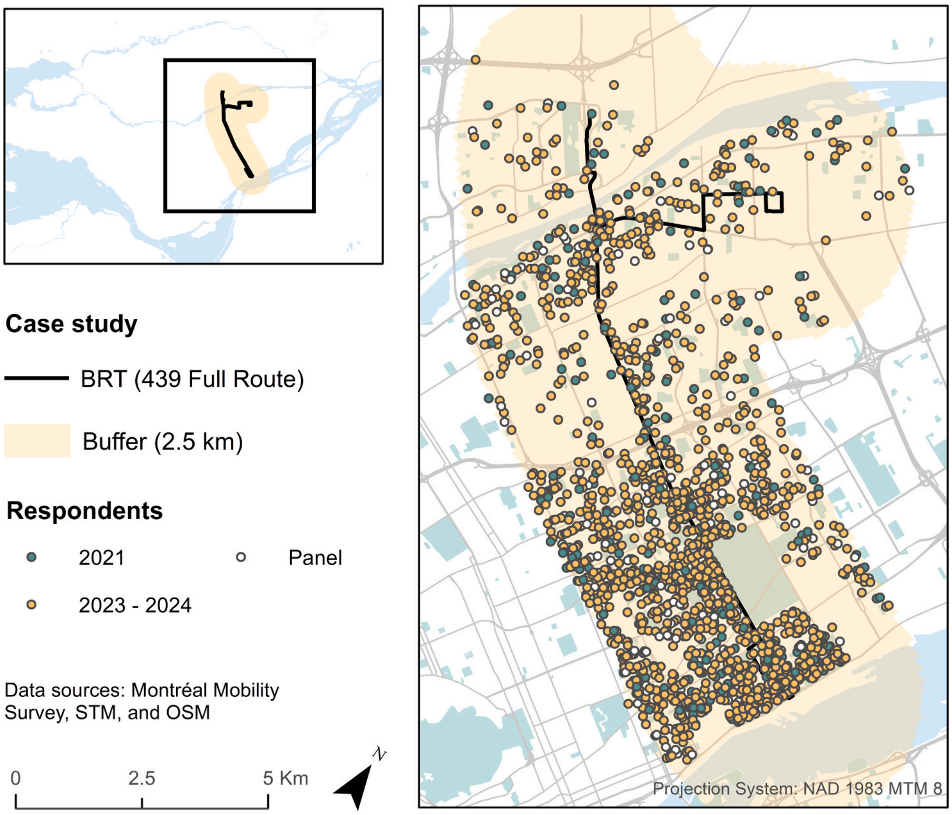

Fig. 2. Sample distribution of respondents along the Pie-IX BRT route path (2.5 km buffer interpreted as a multi-modal access area: walk at shorter distances, cycling, and transit connections).

indicators; (ii) apply weighted k-means clustering to identify market profiles within each period and align profiles across periods using centroid comparisons on shared dimensions; and (iii) use the panel sample to model (a) the likelihood of remaining in the same profile (binary logistic regression) and (b) the intention-behavior gap (multinomial logistic regression). All descriptive and model-based inference relies on survey weights and panel calibration weights to account for differences in sample composition across waves.

4.1. Factor analysis

To reduce the dimensionality of the survey data, we conducted an exploratory factor analysis (EFA) separately on the pre-implementation (2021) and post-implementation (2023–2024) cross-sectional samples. EFA identifies a smaller number of latent constructs or factors based on the underlying covariance among observed variables, allowing for dimensionality reduction with minimal loss of information (Hair et al., 2014). The EFA was estimated using a shared set of segmentation indicators measured with identical wording and response scales across periods, covering (i) attitudes toward the Pie-IX BRT (e.g., perceived benefits), (ii) mobility resources and recent travel behavior (e.g., car access and past-week mode shares for driving and transit), and (iii) neighborhood preference items (e.g., walkability and proximity to services and public transit). For readability, the full item wording and measurement scales are reported alongside the factor solution and loadings in the Results section. Unless otherwise noted, items were measured on a 5-point Likert scale with a neutral midpoint. We used a principal factor extraction method, implemented via the *psych* and *factoextra* packages in R, based on Pearson correlation matrices.

The number of factors to retain was determined using the latent root criterion (eigenvalues $\geq$1) and parallel analysis, which has been shown to outperform scree plots in selecting the appropriate number of components (Zwick and Velicer, 1986). To enhance interpretability and reduce cross-loadings, varimax rotation was applied. Indicators were retained only if their factor loadings met or exceeded a conservative threshold of 0.50, ensuring practical and statistical significance given the sample size (Hair et al., 2014). Prior to extraction, we verified factorability using three diagnostic measures: moderate inter-item correlations ($r \geq 0.30$), a KMO measure $\geq$ 0.70, and a statistically significant Bartlett's Test of Sphericity. Because EFA was estimated separately for pre- and post-implementation samples, factor structures could differ across periods. Therefore, we assessed cross-period factor stability by comparing the rotated loading patterns and computing Tucker's coefficients of congruence after aligning corresponding factors. Factors demonstrating acceptable cross-period similarity were retained for clustering to facilitate meaningful comparisons of market profiles over time.

4.2. Segmenting market profiles using weighted K-means cluster analysis

To identify distinct transit market profiles, we applied a weighted k-means clustering algorithm to a combination of factor scores supplemented by three additional measures capturing telecommuting frequency, gentrification concerns, and BRT adoption (intention/usage). K-means is a clustering technique based on a centroid algorithm, where each observation is assigned to the cluster with the nearest mean value across the selected dimensions. Cluster centroids are updated iteratively to minimize within-group variance while maximizing between-group differences (Hair et al., 2014).

Clustering was performed separately for the pre-implementation (2021) and post-implementation (2023–2024) samples to allow profiles to be identified within each period while maintaining comparability through using the same indicators at both points in time. In the pre-BRT segmentation, we clustered respondents using factor scores from the exploratory factor analysis (described in Section 4.1), complemented with three additional variables: telecommuting frequency over the past seven days, gentrification concerns, and stated intention to use the BRT. Gentrification concerns were measured with the item, *"I am concerned about whether I will be able to remain in my neighborhood because of rising costs,"* and intention was measured by asking, *"How likely are you to use the Pie-IX BRT for any reason when it is complete and operational?"* Both items were collected on a 5-point Likert scale. For the post-BRT segmentation, we retained the four comparable factor scores and again included telecommuting frequency and gentrification concerns; however, intention was replaced with self-reported frequency of BRT use (*daily; more than once a week; a few times a month; once a month; less than once a month; tried it out; never*). All clustering inputs were standardized within period using the *scale* function in R to ensure equal contribution to the clustering solution.

After estimating clusters in each period, we aligned segment labels across time by comparing standardized centroid profiles on the shared dimensions and verifying that each segment retained consistent defining characteristics. Because variables were standardized within each period, centroid magnitudes cannot be compared directly across time. Accordingly, clusters were aligned based on similarity in centroid profile shape (relative highs/lows across dimensions) rather than on exact centroid values; we then validated the alignment by confirming that matched clusters exhibited comparable descriptive patterns on each profile core defining variables (e.g., telecommuting patterns, mobility resources, and travel behavior).

The clustering was implemented using the *kcca* function from the *flexclust* package in R, which supports observation-level survey weights. Sample weights were developed using the *anesrake* package (Pasek, 2018), based on an iterative proportional fitting (raking) algorithm (DeBell and Krosnick, 2009) that aligns each wave's analytic sample with 2021 Canadian Census marginal distributions of age group, gender, and household income along the Pie-IX BRT corridor at the dissemination area level. Although the same recruitment approach was used across waves, unweighted sample composition varies by wave (Table 1); therefore, each wave was calibrated separately to the same corridor-level census benchmarks. To limit the influence of extreme weights, raking used a maximum weight cap (10), and we inspected weight distributions and post-raking margins to confirm alignment with the targets. The resulting weights showed moderate dispersion (approximately 0.34 to 4.56 in 2021 and 0.22 to 2.32 in 2023–2024). Raking targets were obtained from Statistics Canada's 2021 Census (Statistics Canada, 2023) and retrieved using the *cancensus* package (von Bergmann et al., 2021).

To determine the optimal number of clusters, we tested solutions ranging from three to eight groups, as suggested by Damant-Sirois et al. (2014). Cluster selection followed transit-specific criteria proposed by Krizek and El-Geneidy (2007) and later applied by Van Lierop and El-Geneidy (2017). These criteria include cluster distinctiveness, relevance to transport planning, consistency with prior research, and interpretability. In addition, silhouette analysis was used to evaluate the separation between clusters and guide final selection. The derived market profiles provide the basis for assessing longitudinal market stability and modeling behavioral alignment with stated intentions in the subsequent analyses.

4.3. Binary logistic regression: Likelihood of remaining in the same cluster profile

To examine whether individuals remained in the same cluster profile over time, we used the longitudinal panel subsample ($n = 209$) observed both before and after the BRT opened. Panel respondents were assigned to cluster profiles using the period-specific cross-sectional segmentation solutions estimated in Sections 4.1 and 4.2: cluster membership at baseline comes from the 2021 segmentation and cluster membership at follow-up comes from the 2023–2024 segmentation, matched to each respondent's most recent post-implementation observation. This approach preserves the period-specific definitions of cluster profiles and avoids re-estimating factor and clustering models on the smaller panel subsample for inference. As a robustness check, we replicated the factor and clustering steps on the panel subsample and found a comparable set of profiles, consistent with the cross-sectional solutions.

To mitigate differences between the panel subsample and the corridor population arising from non-random participation and attrition, we derived panel calibration weights using iterative proportional fitting (raking). The panel was calibrated to corridor census benchmarks for baseline age, gender, and income, and to the weighted cross-sectional segment shares pre- and post-BRT implementation. No constraints are imposed on transition paths, which remain identified from the observed panel transitions. Therefore, this procedure does not create synthetic observations or impute transitions; it only re-weights observed respondents. To limit the influence of extreme weights, raking used a maximum weight cap (cap = 10). Weight distributions and post-raking margins were inspected to confirm agreement with the targets.

We then estimated weighted binary logistic regression models in which the dependent variable indicates whether a respondent remained in the same aligned market profile between the pre- and post-BRT waves (1 = retained; 0 = transitioned). Three model specifications are estimated. Model 1 includes baseline profile indicators only. Model 2 adds a set of baseline characteristics measured in the pre-BRT wave (i.e., age, gender, household income group, and distance to the nearest BRT station) to assess whether these factors improve ability to distinguish between retainers and switchers beyond baseline profile membership. Model 3 extends Model 2 by adding life-transition indicators capturing changes in circumstances plausibly related to mobility and market membership (household size, child/household structure, car access, employment status, telecommuting frequency, income, and residential relocation relative to the corridor, measured as a $\geq$0.5 km change in distance to the BRT). All models are estimated with a binomial logit link and the panel calibration weights. These specifications allow us to assess whether baseline profiles, baseline circumstances, and observed life transitions provide incremental explanatory value for profile retention versus switching.

4.4. Multinomial regression: Modeling the intention-behavior gap

To examine the alignment between respondents' stated intentions and their subsequent behavior, we estimated a multinomial logistic regression model using the panel sample. The dependent variable captures four mutually exclusive intention-behavior categories defined using baseline intention (pre-implementation) and subsequent BRT usage (post-implementation): (1) intended and used the BRT, (2) intended but did not use, (3) did not intend but used, and (4) did not intend and did not use. This classification enables a

Table 2
Factor loadings for the pre-BRT implementation sample.

Factor	Variable	Loadings	Cronbach Alpha
Pie-IX BRT perceived benefits	The Pie-IX BRT is a good thing for the Greater Montreal area	0.809	0.834
	The Pie-IX BRT is a good thing for the environment	0.857	
	The Pie-IX BRT is a good thing for business	0.662	
Car-oriented mobility	Being in a neighborhood where it is practical to move around and park by car, traffic is light, there is good access by car, payment and availability for parking was an important factor in my decision to move into my current home	0.671	0.535
	I have regular access to at least one private automobile in my household [Yes/No]	0.701	
	Driving mode share in the past week [% of trips]	0.663	
Walkable neighborhood preference	Being in a neighbourhood where it is pleasant to walk was an important factor in my decision to move into my current home	0.625	0.714
	Being near shops and services was an important factor in my decision to move into my current home	0.601	
	Being near public transport was an important factor in my decision to move into my current home	0.571	
	Presence of parks and green spaces was an important factor in my decision to move into my current home	0.673	
Transit reliance	Do you have a monthly transit pass? [Yes/No]	0.658	0.613
	Transit mode share in the past week [% of trips]	0.776	

Variance Explained (52.7%); KMO (0.74); Bartlett's Test of Sphericity ($\chi2 = 2053.684$, d.f. = 66, p-value < 0.001).

detailed analysis of factors associated with consistency and inconsistency between intention and behavior. The explanatory variables and weighting procedures are consistent with those described in Section 4.3, and models were estimated using the panel calibration weights. This step examines associations between baseline characteristics measured prior to implementation and subsequent intention-behavior outcomes.

5. Results and discussions

5.1. Market profiles

To assess how attitudinal and behavioral patterns evolved between the pre- and post-implementation periods for the Pie-IX BRT, this section presents the factor structures used to segment the market and the resulting market profiles identified before and after implementation.

5.1.1. Exploratory factor analysis

Tables 2 and 3 present the results of the exploratory factor analyses for the pre- and post-BRT implementation samples, respectively. In the pre-BRT period, four factors were identified: perceived benefits of the Pie-IX BRT, car-oriented mobility, walkable neighborhood preference, and transit reliance. These constructs capture (i) general support for the Pie-IX BRT and its perceived benefits (regional, environmental, and economic), (ii) a car-oriented mobility context and behavior, reflected in prioritizing car-friendly neighborhood characteristics, having car access, and a higher share of recent trips by car, (iii) a preference for walkable, amenity-rich neighborhoods, reflected in valuing walkability, proximity to services, parks/green space, and public transit, and (iv) reliance on public transit, reflected in monthly pass ownership and a higher share of recent trips by transit. These factors were then used as inputs to the clustering procedure to identify distinct market profiles. Together, these latent constructs accounted for 52.7% of the total variance. Internal consistency for car-oriented mobility was lower ($\alpha = 0.535$), which is not unexpected given the small number and mixed nature of indicators; however, all retained items loaded strongly ($\geq$0.60) on a single factor and the construct was conceptually coherent for segmentation purposes. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.74, and Bartlett's Test of Sphericity confirmed the appropriateness of factor extraction ($\chi2 = 2053.684$, $p < 0.001$). Factor solutions are reported after varimax rotation.

In the post-BRT sample, a similar structure emerged, with four factors extracted: perceived benefits of the Pie-IX BRT, car-oriented mobility, walkable neighborhood preference, and transit reliance. The extracted factors explained 54.5% of the total variance, with similar levels of internal consistency to the pre-implementation sample. The sample remained adequate for factoring (KMO = 0.78; Bartlett's $\chi2 = 7132.116$, $p < 0.001$).

Beyond identifying the same four-factor structure in both periods, we formally assessed cross-period factor stability using Tucker's coefficients of congruence computed from the full loading matrices (using the rotated solutions) after aligning corresponding factors across periods, where values closer to 1 indicate stronger similarity. Congruence coefficients indicated excellent similarity for all four constructs ($\varphi = 0.997$ for Pie-IX BRT perceived benefits; $\varphi = 0.994$ for car-oriented mobility; $\varphi = 0.988$ for walkable neighborhood preference; and $\varphi = 0.985$ for transit reliance), supporting measurement comparability of the extracted factor structure for pre- versus post-implementation market segmentation.

5.1.2. Market profiles

Using the EFA-derived factor scores together with three additional variables (telecommuting frequency, gentrification concerns,

Table 3
Factor loadings for the post-BRT implementation sample.

Factor	Variable	Loadings	Cronbach Alpha
Pie-IX BRT perceived benefits	The Pie-IX BRT is a good thing for the Greater Montreal area	0.828	0.844
	The Pie-IX BRT is a good thing for the environment	0.818	
	The Pie-IX BRT is a good thing for business	0.710	
Car-oriented mobility	Being in a neighborhood where it is practical to move around and park by car, traffic is light, there is good access by car, payment and availability for parking was an important factor in my decision to move into my current home	0.663	0.552
	I have regular access to at least one private automobile in my household [Yes/No]	0.682	
	Driving mode share in the past week [% of trips]	0.607	
Walkable neighborhood preference	Being in a neighbourhood where it is pleasant to walk was an important factor in my decision to move into my current home	0.618	0.745
	Being near shops and services was an important factor in my decision to move into my current home	0.696	
	Being near public transport was an important factor in my decision to move into my current home	0.652	
	Presence of parks and green spaces was an important factor in my decision to move into my current home	0.617	
Transit reliance	Do you have a monthly transit pass? [Yes/No]	0.603	0.665
	Transit mode share in the past week [% of trips]	0.861	

Variance Explained (54.5%); KMO (0.78); Bartlett's Test of Sphericity ($\chi2 = 7132.116$, d.f. = 66, p-value < 0.001).

and the BRT adoption indicator), we estimated weighted k-means solutions separately for the pre-implementation (2021) and post-implementation (2023–2024) samples. A four-cluster solution was selected in each period based on interpretability and separation diagnostics (Section 4.2) and is summarized in Figs. 3 and 4. Clusters were labeled based on their most defining characteristics on the standardized clustering dimensions. In the pre-implementation sample, the identified clusters were labeled as transit-reliant potential user, telecommuter potential choice rider, walkability-oriented individual, and car-oriented individual. These profiles differed in attitudinal orientations, mobility resources, and predisposition toward adopting the BRT (see Appendix A2 for detailed socio-demographic characteristics).

In the post-implementation period, we recovered a broadly similar set of clusters. The post-BRT market was composed of transit-reliant BRT rider, telecommuter choice rider, walkability-oriented individual, and car-oriented individual profiles (see Appendix A3 for detailed socio-demographic characteristics). Profile labels were aligned across periods by comparing centroid patterns on the shared standardized clustering dimensions. The only planned non-equivalence across periods is the adoption indicator, measured as stated intention pre-implementation and reported BRT use post-implementation. Overall, the four-profile structure was broadly comparable across periods; within the tested solutions, we did not identify an additional distinct profile in the post-implementation data. This alignment does not mean the clusters contain the same people or the same averages over time. Rather, each cluster displays a similar pattern on the shared segmentation dimensions relative to the other clusters in that period.

5.1.2.1. Pre-BRT Markets. Clusters were derived from the segmentation indicators described in Section 4.2; additional variables are reported descriptively to profile each segment.

Transit-reliant potential user (19%): This group is characterized by strong dependence on public transit and a high predisposition to adopt the Pie-IX BRT once operational. Only 40.1% report access to at least one private automobile, and their recent mode share is dominated by transit (57%) with limited car use (11%) over the last 7 days. They tend to live close to the planned infrastructure (1.4 km on avg.) and report high stated intention to use the BRT (83.0%). Expected travel-time savings are the most frequently cited motivator (54.8%). However, among those without intention to use the BRT, the dominant reason is a lack of fit with desired destinations (65.7% cite 'it won't go where I want to go'). Demographically, the segment is slightly more female (53.3%) and largely working age (88.9% aged 18–64), with a lower-to-middle income profile (53.7% below 60 k CAD; 34.7% between 60–120 k). Members are primarily workers (64.3%), report low telecommuting frequency (0.6 days/week), and express overall support for the BRT being positive for Greater Montreal (83.9%). The segment also includes a sizeable share of students (21.6%).

Telecommuter potential choice rider (23%): They are defined by comparatively high telecommuting frequency and a high stated intention to use the Pie-IX BRT once operational, while maintaining substantial access to private automobiles. This segment reports the highest level of telecommuting (1.5 days avg. over the last 7 days), with high household car access (87.8%) and a comparatively high prevalence of households with children (31.1%). Their recent mode share reflects a mixture of car and active travel (46% car share and 45% active share, on average), with limited transit use (8%). The group is primarily working age (31.3% aged 18–35 and 51.2% aged 36–64) and skews toward higher-income households (29.4% reporting incomes over 120 k CAD), with a large share employed (76.5%). Despite low recent transit use (8% mode share), stated intention to use the BRT is high (78.2%), with expected travel-time savings cited as a key motivator (40.2%). Separately, overall support for the project is strong (95.5%); however, among those without intention to use the BRT, the dominant reason is a lack of fit with desired destinations (84.5% cite "it won't go where I want to go").

Walkability-oriented individual (28%): Those in this group display a strong orientation toward active travel, consistent with its label. Active modes account for most recent trips (84% over the last 7 days), with minimal car and transit use (8% and 5%) and low access to private automobiles (32.1% reporting at least one vehicle in the household). The segment is largely working age (35.5% aged 18–35; 49.6% aged 36–64) and leans lower-income (61.2% below 60 k CAD), with most members being workers (58.2%), low telecommuting rates '(0.4 days/week), and a notable share of immigrants (21.4%). They also score higher on gentrification concerns, which may reflect heightened housing affordability concerns in this segment. They live farther to the planned infrastructure compared to the two previous groups (avg. 1.8 km) and show mixed intention to use the BRT (48.4%), most commonly motivated by expected travel-time savings (31.4%); among those without intention, the dominant reason is that the service does not align with desired

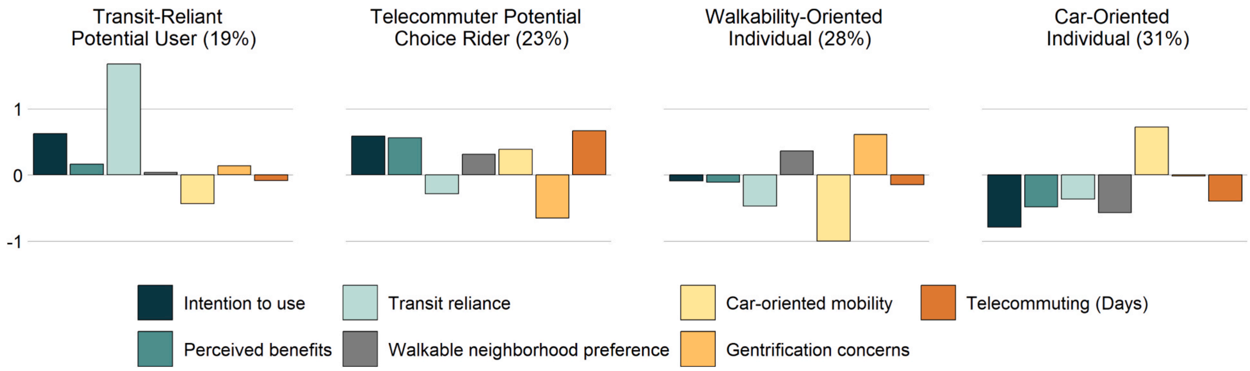

Fig. 3. Identified market profiles pre-BRT implementation.

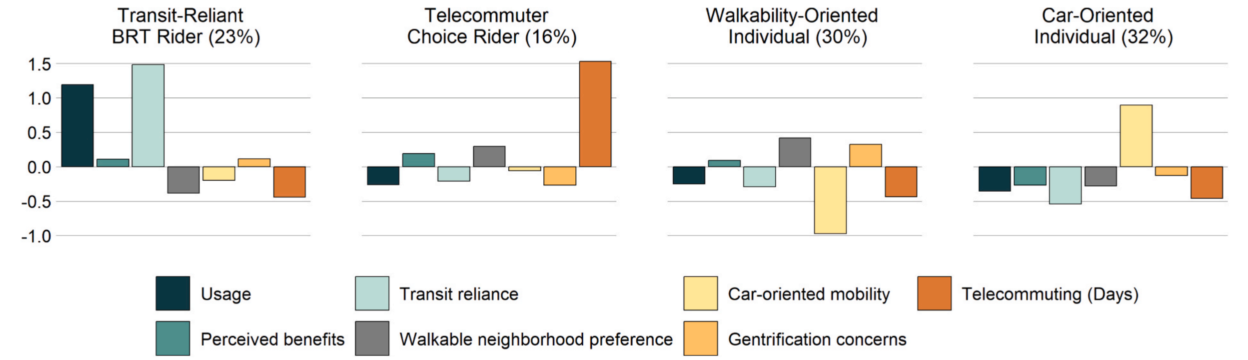

Fig. 4. Identified market profiles post-BRT implementation.

destinations (78.6% cite "it won't go where I want to go"). Overall support for the BRT being positive for Greater Montreal remains high (82.9%).

Car-oriented individual (31%): This group is defined by high reliance on private automobiles and minimal engagement with public transit. Nearly all report access to at least one private vehicle (97.6%), and their recent travel is predominantly car-based (77% car share over the last 7 days), with limited active travel (17%) and very low transit use (4%). This segment is older than other profiles, with a sizable share aged 65 and over (35.3%), and includes a relatively large retired population (38.0%); they also report the highest prevalence of disability (24.1%). They live furthest from the planned infrastructure, 2.0 km on average, and show limited predisposition to adopt the BRT (16.9% intention to use). Among those without intention, the dominant reason given is that the service does not align with desired destinations (65.4% cite "it won't go where I want to go"). Overall support for the BRT being positive for Greater Montreal is comparatively lower in this segment (65.0%).

5.1.2.2. Post-BRT Markets. Profiles are aligned across periods based on centroid patterns on the shared standardized dimensions.

Transit-Reliant BRT rider (23%): Overall, this segment closely resembles the pre-implementation *transit-reliant potential user* profile in its defining characteristics. The group is characterized by low automobile access and transit-dominant travel: only 36.8% report access to at least one private vehicle, and recent travel is primarily transit-based (70% transit share over the last 7 days), with limited car use (10%) and a modest active share (20%). They live close to the corridor (avg. 1.1 km to the nearest station), and 86.9% report having used the Pie-IX BRT. Among users, the most frequently cited reasons for using the BRT were travel-time savings and service replacement; among non-users, the most common barrier was lack of fit with desired destinations. The segment remains skewing younger (53% aged 18–35), slightly more female (55.6%), and lower-income (63.2% below 60 k CAD).

Telecommuter choice rider (16%): This segment corresponds closely to the pre-implementation *telecommuter potential choice rider* profile in its defining characteristics. They report the highest telecommuting frequency (avg. 4.3 days over the last 7 days) and comparatively high access to private automobiles (62.7%). Their recent travel reflects a split between active (60%) and motorized modes (20% car; 20% transit). They live moderately close to the corridor (mean 1.4 km), and 50.9% report having used the Pie-IX BRT. Among users, travel-time savings was the most frequently cited reason for using the BRT, while among non-users the main barrier was lack of fit with desired destinations; overall support for the project remains high (84.5%).

Walkability-oriented individual (30%): Consistent with its pre-implementation counterpart in its defining characteristics, this segment is defined by active-travel dominance and very limited reliance on private automobiles: only 17.5% report access to at least one private vehicle, and recent mode share is overwhelmingly active (80% over the last 7 days). They live moderately close to the corridor (avg. 1.5 km to the nearest station), and 59.1% report having used the Pie-IX BRT. Among users, travel-time savings was the most frequently cited reason for using the BRT, followed by service replacement; among non-users, the most common barrier was lack of fit with desired destinations. The segment leans lower-income (61.4% below 60 k CAD) and shows comparatively higher concern about displacement and rising housing costs (gentrification), while overall support for the project remains high (85.3%).

Car-oriented individual (32%): This segment represents the post-implementation counterpart of the pre-implementation *car-oriented individual* profile based on its defining characteristics. The group is defined by high reliance on private automobiles and limited use of public transit: 96.5% report access to at least one private vehicle, and recent travel is predominantly car-based (60% car share over the last 7 days), alongside active travel (30%) and limited transit use (10%). This segment has the lowest share reporting BRT use (39.9% report having used the Pie-IX BRT). Among users, travel-time savings and service replacement were the most frequently cited reasons for using the BRT, while among non-users the most common barrier was lack of fit with desired destinations. Demographically, the segment skews older (32.1% aged 65 and over) and includes a sizeable retired share (32.3%), with comparatively lower overall support for the BRT being positive for Greater Montreal (71.6%).

Taken together, the segmentation results reveal a comparable set of market profiles before and after the implementation of the Pie-IX BRT. While modal behavior and demographic composition shifted slightly within some groups, the segmentation results indicate a broadly comparable set of market profiles before and after implementation. Within the tested solutions, we did not identify an additional distinct profile in the post-implementation data. To better understand profile retention and transitions at the individual level, the following section uses the longitudinal panel to model the likelihood of remaining in the same profile between baseline

(2021) and follow-up (2023–2024) periods using binary logistic regression.

5.2. Profile retention and switching (pre- vs post-BRT)

Although the repeated cross-sectional results suggest broadly similar profile structures before and after implementation, the panel data reveal how individuals actually moved between profiles over time. Using the weighted longitudinal panel (n = 209), we summarize within-person transitions in profile membership between the pre-BRT and post-BRT periods to assess profile retention and switching. Fig. 5 summarizes profile transitions between the pre- and post-BRT waves in the weighted panel.

We report retention rates as the share of respondents who remain in the same aligned market profile across waves (i.e., the same profile defining characteristics). Retention varies substantially across profiles: the *car-oriented* profile is the most stable (87% retained), followed by *walkability-oriented* (64%) and *transit-reliant* (58%), while *telecommuters* are the least stable (36%). Beyond retention, switching is concentrated in a small number of flows (percentages are within-origin): *telecommuters* most often shift toward *walkability-oriented* (31%) and *transit-reliant* (21%) profiles; *walkability-oriented* respondents most commonly shift toward *transit-reliant* (24%); and *transit-reliant* respondents most commonly shift toward *walkability-oriented* (20%). In contrast, *car-oriented* respondents exhibit comparatively limited movement (13% switch), with the main exits toward *telecommuter* (9%) and *walkability-oriented* (4%) profiles. Overall, these findings suggest that while the mobility market around the corridor remains structured around the same four profiles, some profiles are more likely to change than others.

5.2.1. Life transitions among stayers and switchers

To contextualize the market profile transitions shown in Fig. 5, Appendix A4 summarizes before/after descriptive statistics for the longitudinal panel by baseline profile. These descriptives are reported unweighted to describe within-person change (rather than corridor-level distributions). Across the panel, gender composition is essentially unchanged, while the sample ages between the pre- and post-BRT waves (a smaller share aged 18–35 and a larger share aged 65+), consistent with a modest decline in student status and a small increase in retirement. Household sizes are broadly stable, with only a slight increase in the share reporting children in the household. Two factors plausibly linked to profile switching (i.e., car access and proximity to the corridor) show limited aggregate change (car access remains stable and average distance to the BRT is essentially unchanged), suggesting that widespread vehicle acquisition or relocation is unlikely to be the dominant driver of profile transitions in the panel. In contrast, telecommuting increases overall and modal composition shifts modestly toward active travel alongside a small decline in driving share. As a robustness check, the weighted cross-sectional descriptives show the same directional patterns for these main shifts (e.g., higher telecommuting and lower driving share in the post-BRT period), suggesting the panel descriptives are not contradicting broader corridor trends.

Table 4 compares the prevalence of life transitions among respondents who remained in the same market profile (“stayers”) versus those who transitioned to a different profile (“switchers”), using unweighted panel counts to describe observed within-person change.

Switchers are more likely to report at least one transition across the observed dimensions (78% vs. 63% among stayers). Differences are generally modest in absolute terms but directionally consistent across several domains, including telecommuting (48% vs. 37%),

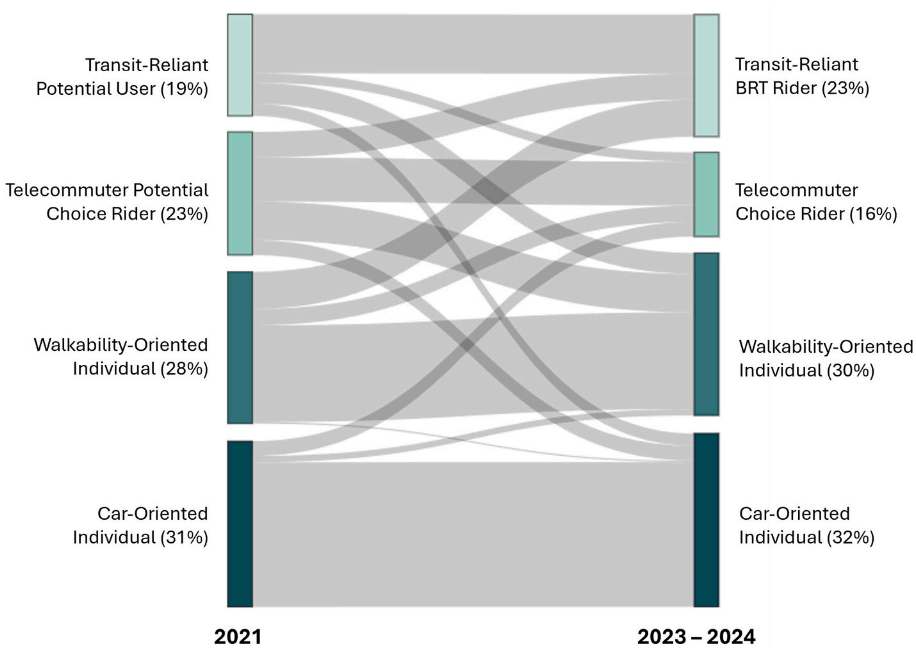

Fig. 5. Market profile transitions in the panel sample (pre- vs post-BRT implementation).

Table 4
Summary of life transition indicators in the panel sample (binary indicators, unweighted sample).

Indicator	Stayers (n = 119)	Switchers (n = 90)
Any life transition	63.0% (n = 75)	77.8% (n = 70)
Income group changed	18.5% (n = 22)	22.2% (n = 20)
Income increased	13.4% (n = 16)	14.4% (n = 13)
Income decreased	5.0% (n = 6)	7.8% (n = 7)
Car access changed	5.0% (n = 6)	12.2% (n = 11)
Gained car access	1.7% (n = 2)	6.7% (n = 6)
Lost car access	3.4% (n = 4)	5.6% (n = 5)
Any employment-status changed	10.9% (n = 13)	15.6% (n = 14)
Became worker	3.4% (n = 4)	3.3% (n = 3)
Stopped working	4.2% (n = 5)	8.9% (n = 8)
Became student	0.0% (n = 0)	1.1% (n = 1)
Stopped being student	3.4% (n = 4)	1.1% (n = 1)
Became retired	2.5% (n = 3)	6.7% (n = 6)
Telecommuting changed	37.0% (n = 44)	47.8% (n = 43)
Telecommuting increased	23.5% (n = 28)	27.8% (n = 25)
Telecommuting decreased	13.4% (n = 16)	20.0% (n = 18)
Household size changed	15.1% (n = 18)	22.2% (n = 20)
Child structure changed	11.8% (n = 14)	16.7% (n = 15)
Distance to BRT changed (≥0.5 km)	5.0% (n = 6)	5.6% (n = 5)

employment-status (16% vs. 11%), and car access (12% vs. 5%). Switchers also show higher rates of household-size change (22% vs. 15%) and changes in child/household structure (17% vs. 12%). Income changes are somewhat more common among switchers (22% vs. 19%), though the direction of change is mixed. By contrast, residential relocation relative to the corridor is rare in both groups (distance-to-BRT change ≥0.5 km: ~6% vs. 5%). Overall, these patterns suggest that profile switching tends to coincide with broader changes in underlying life circumstances rather than being driven by relocation. Profile-wise, the prevalence of at least one life transition is highest among telecommuters (82%), which coincides with lower retention rates, and lowest among car-oriented respondents (55%), with transit-reliant (72%) and walkability-oriented (68%) groups in between. These descriptives are intended as context; the regression models below assess whether these differences persist after accounting for baseline profile membership.

5.2.2. Correlates of profile retention: Weighted binary regression

To examine factors associated with profile retention versus switching between the pre- and post-BRT periods, we estimated weighted binary logistic regression models where the dependent variable indicates whether a respondent remained in the same aligned market profile across waves (1 = retained; 0 = transitioned). Table 5 reports three model specifications: (1) baseline profile only; (2) baseline profile plus baseline sociodemographic covariates; and (3) baseline profile, baseline covariates, and life-transition indicators.

Table 5
Binary logistic regression: Probability of remaining in the same profile.

Variables	Baseline		Socio-demographics		Life Transitions	
	OR	*CI*	*OR*	*CI*	*OR*	*CI*
Intercept	6.85 ***	3.48 – 15.46	9.46 **	2.27 – 43.53	117.09 ***	10.28 – 1775.28
Baseline profile (pre-BRT)						
Baseline [Car-oriented]						
Transit-Reliant	**0.20** **	**0.07 – 0.52**	**0.18** ***	**0.06 – 0.48**	**0.22** **	**0.07 – 0.63**
Telecommuter	**0.08** ***	**0.03 – 0.20**	**0.07** ***	**0.02 – 0.17**	**0.06** ***	**0.02 – 0.16**
Walkability-oriented	**0.26** **	**0.10 – 0.62**	**0.23** **	**0.08 – 0.60**	**0.29** *	**0.09 – 0.80**
Pre-BRT characteristics						
Age			0.99	0.97 – 1.01	**0.96** *	**0.93 – 0.99**
Gender			0.87	0.46 – 1.64	0.99	0.50 – 1.94
Household income						
Below 60 k			0.63	0.22 – 1.71	0.34	0.10 – 1.14
60 – 120 k			1.00	0.37 – 2.67	0.53	0.16 – 1.61
Distance to BRT station (km)			1.27	0.93 – 1.78	1.32	0.92 – 1.96
Life transitions						
Change in household size					0.5	0.18 – 1.38
Change in children status					0.49	0.15 – 1.63
Change in distance to BRT (0.5 km or more)					0.59	0.08 – 3.92
Change in car access					**0.29** *	**0.08 – 0.97**
Change in employment status					0.34	0.11 – 1.10
Change in telecommuting frequency					0.47	0.17 – 1.23
Change in income					1.39	0.56 – 3.55
Observations	209		209		209	
Tjur's R^2	0.140		0.160		0.189	

*p < 0.05 **p < 0.01 ***p < 0.001.

The car-oriented profile serves as the reference category within the baseline profile memberships. We use this reference because it is the most stable group (as shown in Fig. 5) and because prior work consistently links habitual car use to more entrenched travel routines, which are shaped by convenience and car-oriented land design, that can limit responsiveness to modal alternatives even when viable (Bamberg and Schmidt, 2003; Schwanen et al., 2012; Thøgersen, 2006). Moreover, descriptive checks of self-reported trip destinations over the past week (e.g., work, school, shopping, and healthcare) show broadly similar destination shares across profiles. While these data do not allow us to test origin–destination distances or accessibility conditions directly, they suggest that the higher stability of the car-oriented profile is not primarily driven by major differences in trip-purpose composition alone but consistent with persistence in underlying mobility resources and routines. Fig. 5 and the regression models use the same panel calibration weights (Section 4.3).

Across specifications, baseline profile membership is the strongest and most consistent predictor of retention. Relative to the *car-oriented* reference, respondents classified as *telecommuters* at baseline have markedly lower odds of remaining in the same aligned profile, while *transit-reliant* and *walkability-oriented* respondents also show reduced odds of retention, ceteris paribus. These model-based differences mirror the descriptive transition patterns in Fig. 5. This pattern is also consistent with theories of habitual travel behavior (Verplanken et al., 2002): profiles anchored in stable mobility resources and routines, such as the car-oriented group's dominant driving orientation, may be more persistent over time, whereas profiles characterized by more variable activity-travel patterns (notably among *telecommuters*) are more likely to reconfigure. Importantly, baseline profiles reflect the pandemic context, when telecommuting was elevated; it is therefore plausible that many baseline telecommuters subsequently re-adjusted their activity patterns as pandemic conditions eased. Consistent with this interpretation, the panel descriptives indicate that telecommuting decreases are concentrated among switchers in the telecommuter baseline group.

Adding baseline covariates yields only modest improvements in model discrimination relative to the baseline-profile-only specification. We assess discrimination using Tjur's R2 (also called the coefficient of discrimination), which summarizes the separation in predicted probabilities between observed retainers and switchers (larger values indicate better separation). The limited gain suggests that many baseline differences associated with retention are already embedded in the profile classification itself, which captures bundles of attitudes, mobility resources, and travel behavior.

Introducing life-transition indicators add only modest explanatory power beyond baseline profile membership. This should be interpreted considering the panel size (n = 209) and the low frequency of several transitions, which limit statistical power and produce wide confidence intervals for the transition effects. Even so, the estimated directions are broadly consistent with Table 5, where switchers more often report at least one life transition. Changes in mobility resources (most notably car-access) are associated with lower odds of remaining in the same profile, which is conceptually plausible given the central role of vehicle access in mode choice. Other transitions (employment/telework/household composition/relocation) generally point in the expected direction but cannot be estimated precisely enough in this sample.

Taken together, these findings highlight that while market profiles remain stable in aggregate, individual transitions vary across

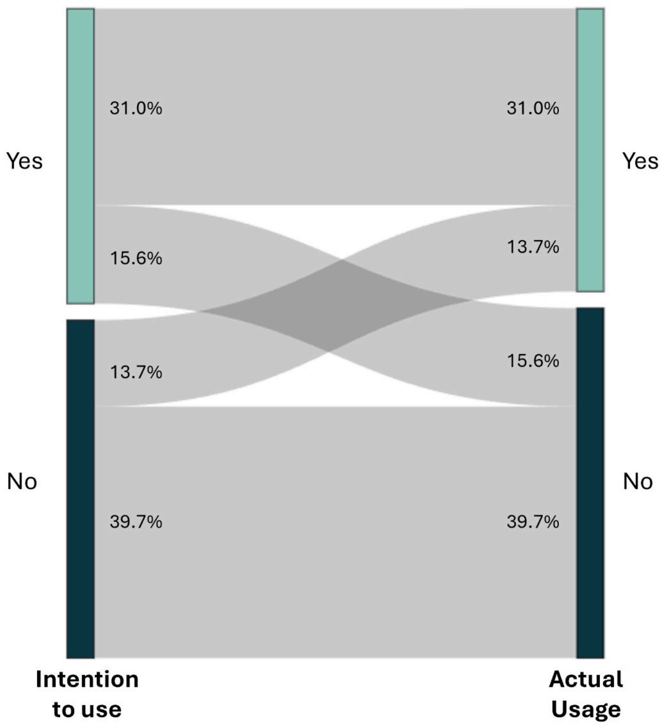

Fig. 6. Intention-behavior gap regarding the Pie-IX BRT.

user types. This is useful for transit agencies because it implies that BRT implementation can be planned around relatively stable segments while recognizing that some profiles are more prone to change and may require more adaptive approaches. Building on these insights, the next section turns to the question of behavioral alignment, examining whether individuals who expressed an intention to use the Pie-IX BRT actually followed through post-implementation.

5.3. The intention-behavior gap

To assess how stated intentions translated into subsequent BRT use, we examine the intention-behavior gap using the weighted panel sample (n = 209). Fig. 6 summarizes the alignment between pre-BRT intention and post-BRT reported use of the Pie-IX BRT. Overall, 31.0% of respondents followed through on their intention to use the Pie-IX BRT (Yes → Yes), while 39.7% remained consistent non-users (No → No). The remaining 29.3% exhibit a mismatch between intention and behavior: 15.6% intended to use the BRT but did not (Yes → No), and 13.7% reported using the service despite initially indicating no intention to do so (No → Yes). These patterns affirm the presence of an intention-behavior gap, consistent with previous findings in behavioral and transportation research (Ajzen, 1991; Sheppard et al., 2002).

To examine which factors are associated with different intention-behavior outcomes, we estimated a weighted multinomial logistic regression model with four categories: consistent non-use (No → No), follow-through (Yes → Yes), abandoned intention (Yes → No), and unexpected adoption (No → Yes) (Table 6). The No → No category is the reference outcome, so coefficients capture differences in the relative likelihood of each outcome compared with consistent non-use.

Market-profile membership is entered as a key explanatory factor, with the *car-oriented* profile as the reference category to maintain consistency with Section 5.2. We also include baseline access and a small set of life-transition indicators to assess whether changes in circumstances between waves are associated with intention-behavior alignment. All models use the panel calibration weights described in Section 4.3. Market-profile membership in this model is defined at baseline (pre-BRT) using the 2021 segmentation; therefore, coefficients compare intention-behavior outcomes across respondents classified into different baseline profiles within the same panel sample, without assuming that profile membership is fixed over time (profile retention/switching is examined separately in Section 5.2). Odds ratios above 1 indicate a higher likelihood of the given outcome (relative to No → No), whereas odds ratios below 1 indicate a lower likelihood. Given the modest panel size and small counts in some outcome-profile combinations, we interpret estimates cautiously and emphasize direction and robustness rather than magnitude.

Yes → Yes (Follow-through on intentions)

Respondents classified as *transit-reliant* at baseline were markedly more likely to follow through on their initial positive intention (Yes → Yes) compared to the *car-oriented* reference group (OR = 3,222.4, $p < 0.001$), ceteris paribus. Respondents classified as *telecommuters* (OR = 59.2, $p < 0.001$) and *walkability-oriented* (OR = 13.7, $p = 0.002$) at baseline also showed significantly higher odds of follow-through relative to *car-oriented individuals*. These results are consistent with the idea that follow-through is more likely when stated intentions align with underlying mobility needs and predispositions toward transit use, in line with the Theory of Planned Behavior (TPB) emphasis on attitudes and perceived behavioral control as drivers of action (Ajzen, 1991, 2011).

Structural and resource constraints remain important. Greater distance to the BRT station is strongly and consistently associated with lower odds of follow-through (OR = 0.15, $p < 0.001$), suggesting that even motivated respondents may fail to act when practical access is constrained. Resource instability also matters: any change in car access between waves is associated with lower odds of follow-through ($p = 0.002$), consistent with the idea that shifts in household mobility resources can disrupt plans and routines and weaken intention-behavior alignment. While these estimates are based on a modest panel and some uncertainty remains for smaller transition subgroups, the overall pattern reinforces the combined importance of baseline market orientation and structural access conditions in translating intention into behavior. At the same time, the small number of car-oriented respondents in the Yes → Yes

Table 6
Multinomial regression: The intention-behavior gap.

Variable	Yes → Yes		Yes → No		No → Yes	
	OR	*p-value*	*OR*	*p-value*	*OR*	*p-value*
Intercept	2.32	0.146	0.71	0.592	0.44	0.213
Cluster before opening						
Baseline [Car-oriented]						
Transit-Reliant	**3,222.42**	**<0.001**	**337.97**	**<0.001**	**55.24**	**0.013**
Telecommuter	**59.17**	**<0.001**	**17.75**	**<0.001**	3.28	0.16
Walkability-oriented	**13.70**	**0.002**	**5.00**	**0.04**	2.20	0.274
Pre-BRT characteristics						
Distance to BRT station (km)	**0.15**	**<0.001**	**0.30**	**<0.001**	**0.40**	**0.005**
Life transitions						
Change in car access	**0.03**	**0.002**	**0.12**	**0.018**	0.85	0.824
Change in telecommuting frequency	0.45	0.199	1.14	0.828	**3.80**	**0.024**
Change in income	1.10	0.883	**3.66**	**0.025**	2.67	0.093

Observations (N = 209); R^2/R^2 adjusted: 0.333/0.329; *$^*p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$.*

category suggests that follow-through into BRT use was limited among this group in our panel, indicating that initial BRT uptake was more strongly associated with respondents already predisposed toward transit use than with more car-oriented individuals.

Yes → No (Abandoned intention)

Relative to the *car-oriented* reference group, respondents in the *transit-reliant*, *telecommuter,* and *walkability-oriented* profiles at baseline show higher odds of intending to use the BRT but not following through (Yes → No), indicating that intention does not translate into adoption uniformly across baseline market profiles. This pattern is consistent with prior work highlighting the limits of intention alone as a predictor of behavior (Sheppard et al., 2002): even when respondents express willingness, follow-through can be undermined by day-to-day constraints and the effort required to establish new routines (Cain and Flynn, 2013; Thøgersen, 2006).

Structural conditions again matter. Greater distance to the BRT station is associated with lower odds of the abandoned-intention outcome relative to persistent non-intention (No → No), suggesting that distance primarily discourages intention formation. At the same time, when focusing on follow-through among baseline intenders (i.e., comparing Yes → No to Yes → Yes), the coefficients imply a higher likelihood of abandonment with increasing distance, which is consistent with access constraints affecting follow-through. In addition, income change is significantly associated with abandoned intention ($OR = 3.66$, $p = 0.025$), suggesting that shifts in household economic circumstances can disrupt planned travel strategies and weaken intention-behavior alignment. Meanwhile, any change in car access is associated with lower odds of the abandoned-intention outcome relative to consistent non-intention (No → No) ($OR = 0.12$, $p = 0.018$), meaning that respondents whose car access changed were more likely to remain in the No → No group than to end up in the Yes → No group. Taken together, the results indicate that "abandonment" may reflect not just weak commitment, but also the interaction between baseline orientation and whether access and resources make BRT use feasible in practice.

No → Yes (Unexpected adopters)

Relative to the *car-oriented* reference group, respondents who were *transit-reliant* at baseline are substantially more likely to adopt the BRT despite initially indicating no intention to use it ($OR = 55.2$, $p = 0.013$), all else equal. While the confidence interval is wide (reflecting the modest panel and small cell counts), the direction is intuitive: individuals already oriented toward transit may be more willing and able to adopt a new service when it becomes available, even if they did not anticipate using it in the pre-period. Structural access also matters. Greater distance to the BRT station is associated with lower odds of unexpected adoption ($OR = 0.4$, $p = 0.005$), consistent with the idea that proximity facilitates low-effort experimentation and reduces practical and psychological barriers (e.g., uncertainty or perceived inconvenience) (Gärling and Schuitema, 2007). In addition, changes in telecommuting frequency are positively associated with unexpected adoption ($OR = 3.8$, $p = 0.024$), suggesting that shifts in activity patterns between waves can create new travel needs or opportunities that prompt adoption even among those who previously expressed no intention. Taken together, these results suggest that "unexpected adoption" is more likely when baseline orientation makes experimentation easier and when practical access and evolving routines support trying the service in practice.

Overall, the model points to a layered process: baseline market profiles shape who is positioned to adopt, while access (distance) and shifts in routines and resources (e.g., telework, car access, income) help explain why intentions translate (or fail to translate) into behavior. These findings empirically support the existence of an intention-behavior gap and show that its magnitude and direction vary by market segment. Fig. 7 provides a descriptive visualization of the four intention-behavior outcomes within each baseline (pre-BRT) market profile. Consistent with TPB and habit theory, behavior is most likely to align with intention when attitudes/needs and structural access conditions match, as seen most clearly among baseline transit-reliant respondents (and, in some cases, baseline telecommuters). Conversely, entrenched routines and structural barriers are associated with lower intention-behavior alignment.

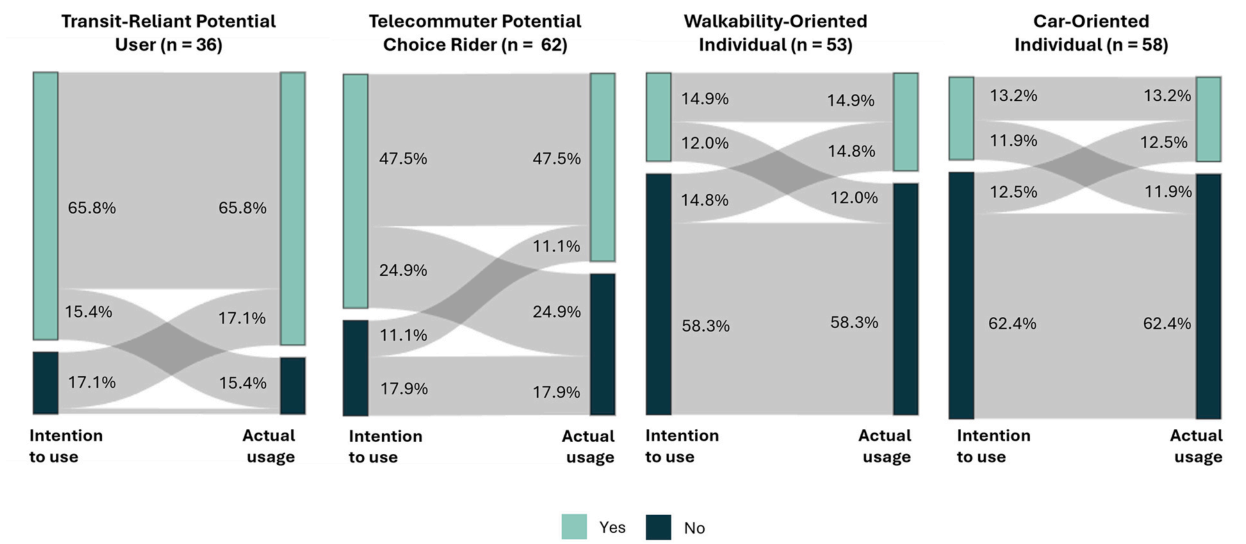

Fig. 7. Intention-behavior gap regarding the Pie-IX BRT by baseline market profile (reported sample sizes are unweighted).

6. Policy implications

Policy discussions around new transit infrastructure often emphasize ridership levels and growth, yet these aggregate patterns do not indicate whether adoption reflects (i) expected adoption among those who intended to use the service or (ii) uptake among those who did not anticipate using it. In the context of a new BRT, pre-opening intentions are formed based on expectations, while post-opening behavior reflects how those expectations interact with practical feasibility once the service is available. This framing is consistent with the Theory of Planned Behavior (Ajzen, 1991, 2011), which indicates that intentions are a necessary precursor to action, but follow-through depends on perceived and actual behavioral control and on contextual conditions that enable the intended behavior.

We organize our policy implications around the intention-behavior pathways examined in this study. These pathways reflect three distinct policy goals: reducing abandoned intention (Yes → No), enabling unexpected adoption (No → Yes), and protecting follow-through (Yes → Yes). Importantly, the market-segmentation results help translate these tasks into actionable groups, by showing that intention-behavior alignment and mismatch are not evenly distributed across baseline profiles. Across pathways, our results point to a small set of recurring mechanisms that appear to influence these intention-behavior outcomes. Most notably, distance to the BRT station is consistently associated with follow-through, abandoned intention, and unexpected adoption, underscoring that access to the service is central for adoption. In addition, between-wave changes in circumstances (e.g., income, car access, and telecommuting) correlate with mismatch and adoption, suggesting that intentions are enacted within evolving routines and constraints, which can help further explain why expressed willingness towards the service does not always translate into observed use.

6.1. *Reducing abandoned intention (Yes → No)*

A key post-implementation challenge is abandoned intention, i.e., individuals who indicated they would use the Pie-IX BRT prior to opening but did not report using it afterward. From a policy standpoint, this group is particularly interesting because the barrier is unlikely to be attitudinal opposition or lack of awareness; rather, it is likely conditioned by constraints that prevent conversion once the service becomes available. Consistent with this interpretation, our results indicate that abandoned intention is associated with a combination of baseline cluster profiles, access, and changing circumstances (i.e., car access and income).

Abandonment can be interpreted through three complementary mechanisms discussed in the literature. First, habit and inertia can limit behavioral change even when intentions are favorable, because established routines reduce deliberation and make switching effortful (Thøgersen, 2006; Verplanken et al., 2002). Second, uncertainty and friction can raise the perceived cost of acting on an intention and increase the likelihood of defaulting to existing routines (Gärling and Schuitema, 2007). Third, resource instability, particularly economic pressures, may alter feasible options or reprioritize travel decisions during periods of change (Allen and Farber, 2020a; El-Geneidy et al., 2016; Mattioli et al., 2017). Consequently, abandoned intentions should be treated less as "weak commitment" and more as a signal that intended adoption is not consistently easy to enact within everyday routines.

Taken together, the empirical findings and theoretical mechanisms suggest two sets of policy implications. First, segment-specific conversion strategies can use the baseline market profiles as targets rather than relying on generic messaging:

- For *telecommuter choice riders*, the goal is to lower the effort threshold required by reducing uncertainty and cognitive costs (Bamberg and Schmidt, 2003; Cain and Flynn, 2013), given likely reliance on car-based routines and reduced necessity to adopt due to telecommuting. This supports low-effort trial initiatives (e.g., limited-time free/discounted rides) and wayfinding that makes first use simple, alongside clear communication of when the BRT is advantageous.
- For *walkability-oriented individuals*, conversion may be more likely when the BRT is positioned as complementary to active travel, including improving walk/bike integration and communicating situations where BRT adds value (e.g., longer or less pleasant trips).
- For *transit-reliant respondents*, abandoned intention should be treated primarily as a signal of lack of compatibility between needs and the service provided rather than a persuasion failure, implying that improving service (i.e., access, wait times, feeder service) may yield higher returns than attitudinal campaigns.

Second, our results indicate that protecting affordability and reducing cost uncertainty is a plausible lever for reducing abandoned intention. In this context, fare policies that make costs more predictable or affordable (e.g., mechanisms such as fare capping or including subsidies for lower-income households) can be framed as strengthening perceived behavioral control for households facing economic pressures, making it easier to follow through on their initial intention rather than abandon them.

6.2. *Increasing unexpected adoption (No → Yes)*

A second policy-relevant pathway is unexpected adoption, i.e., individuals who did not report an intention to use the Pie-IX BRT prior to opening but nonetheless reported using it afterward. From a policy perspective, unexpected adoption is valuable because it captures latent demand: service adoption occurring even without stated pre-opening intention, suggesting that the service can become attractive once it is experienced and integrated into daily mobility options. This is consistent with the notion that pre-opening intentions are formed under uncertainty and may also reflect limited information about practical fit rather than firm opposition to the service.

Unexpected adoption can be interpreted through three complementary mechanisms. First, low-effort experimentation becomes more likely when uncertainty is reduced and the perceived "cost" of trying the service is small (Gärling and Schuitema, 2007). Second, windows of routine disruption can facilitate experimentation: changes in daily schedules or activity patterns weaken existing habits and create moments when travel routines are re-assessed, making new behaviors more likely (Thøgersen, 2006; Verplanken et al., 2002). Third, access conditions are connected to the feasibility of service uptake. In our results, distance to the BRT station is negatively associated with unexpected adoption, indicating that proximity lowers the effort required to experiment and increases the likelihood that occasional use becomes feasible in practice.

Together, these mechanisms suggest three policy implications. First, increasing unexpected adoption requires lowering the barriers to first use by reducing uncertainty and simplifying the "how-to" of trying the service (e.g., clear onboarding information, intuitive wayfinding, and communication focused on what trips the BRT is best suited for). Second, because trial is more likely when routines are changing, information and prompts can be timed to moments when individuals are adjusting schedules and travel patterns (e.g., new residents, start of a school year), when experimentation is more likely to occur. Third, the strong role of distance implies that unexpected adoption is facilitated when station access makes trying the BRT low effort; accordingly, interventions that effectively reduce first/last-mile effort and transfer penalties can support experimentation and broaden the set of users for whom trial is feasible.

6.3. *Sustaining follow-through (Yes → Yes)*

Follow-through reflects intention-behavior alignment and should be protected to foster ridership once the service is available. In our results, follow-through is strongly associated with baseline cluster profiles and related to access conditions, with greater distance to the BRT station and changes in mobility resources (e.g., car access) linked to lower likelihood of intention-behavior alignment, reinforcing that even motivated users may fail to maintain use when perceived feasibility is low. Beyond feasibility, the satisfaction and loyalty literature suggests that initial experiences matter: service quality is consistently linked to satisfaction and loyalty, and negative "critical incidents" can weigh disproportionately on loyalty formation (Allen et al., 2019; Carvalho et al., 2022). Accordingly, protecting follow-through implies not only maintaining access to the service, but also ensuring that early interactions are reliable, so that initial use reinforces perceived value and supports repeated behavior.

Finally, it is important to emphasize that the goal of a post-implementation policy is not universal adoption. For some individuals, non-use reflects a genuine mismatch between their routine destinations and the corridor served by the Pie-IX BRT, and continued non-use may be an efficient outcome rather than a policy failure. In this context, the general policy goal is better framed as reducing avoidable frictions and uncertainty for those for whom the service is feasible and potentially beneficial.

7. Conclusions

This study examined how the transit market evolved in response to the implementation of a new BRT infrastructure through the lens of the intention-behavior concept. Using cross-sectional data and a longitudinal panel tracking individuals living along the BRT route before and after the implementation of the Pie-IX BRT in Montreal, the study combined factor-cluster analysis with regression modeling to assess the stability of user segments and the alignment between pre-implementation intentions and actual behavior. Findings show that while aggregate market profiles remained stable over time, behavioral consistency at the individual level varied across user types. In particular, transit-reliant riders, car-oriented individuals, and walkability-oriented respondents displayed high profile stability, while telecommuter choice riders were significantly more fluid in their travel patterns.

The study provides evidence of an intention-behavior gap regarding the analyzed infrastructure. Nearly one-third of the panel either failed to follow through on their intention to use the BRT or adopted it despite having no initial plans to do so. Regression models revealed that follow-through was most likely among transit-reliant individuals, who reported strong intentions and structural conditions conducive to BRT use (e.g., proximity, car inaccessibility). Conversely, car-oriented individuals were least likely to follow through, reaffirming the behavioral inertia often associated with automobile dependence. Underlying constraints such as distance from the BRT influenced both market stability and adoption patterns, underscoring the interplay between attitudes and contextual limitations. Similarly, changes in life circumstances (car access, income, telecommuting) were associated with lower intention-behavior consistency.

While the analysis offers valuable insights into behavior change, it is not without limitations. First, the longitudinal inference relies on a small panel ($n = 209$), which limits statistical power, particularly for detecting smaller effects, interactions, and the influence of less common life transitions. As noted in the Results section, null findings should be interpreted cautiously, and some transition estimates may be imprecise. Second, although we apply panel calibration weights to mitigate differences arising from non-random participation and attrition, weighting cannot fully address unobserved selection, and the observed associations should not be interpreted as causal effects. Future studies would benefit from larger panel samples, longer follow-up periods, and mixed-method approaches (e.g., qualitative interviews) to further explore the mechanisms behind the uptake of new BRT services.

Overall, this study demonstrates the value of integrating behavioral theory with market segmentation in the evaluation of new transit services. By highlighting where and for whom intention aligns with behavior (and where it does not), it offers a framework for targeted transit planning. As cities continue to invest in sustainable mobility infrastructure, understanding the behavioral dynamics underlying ridership is essential not only for predicting demand but also for designing policies that support long-term adoption.

CRediT authorship contribution statement

Thiago Carvalho: Writing – review & editing, Writing – original draft, Visualization, Validation, 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, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors would like to thank the three anonymous reviewers for their constructive feedback on the earlier version of the manuscript. This research was funded by Natural Sciences and Engineering Research Council of Canada (NSERC RGPIN-2023-03852), Fonds de Recherche du Québec Société et Culture (https://doi.org/10.69777/370079) Canadian Institute of Health Research (CIHR) (CIHR PJT-195797) and the Tier 1 Canada Research Chair in Public Transport Planning and Operation (CRC-2025-00098) and the Social Sciences and Humanities Research Council's partnership grant Mobilizing justice (SSHRC 895-2021-1009).

Appendix

Appendix A1. Literature review of market segmentation studies

Paper	Context	Data	Sample	Clustering Focus	Clustering Variables	Method	**Classification**
Captive, Choice, and Captive by Choice							
Wilson et al. (1984)	Ottawa-Carleton, Canada	Cross-sectional	Transit + Car	Choice/ Captivity	Attitudes	A priori	Captive + Choice
Beimborn et al. (2003)	Portland, OR, USA	Cross-sectional	Transit + Car	Captivity	Behavior + Geography	A priori	Captive + Choice
Krizek and El-Geneidy (2007)	Twin Cities, MN, USA	Cross-sectional	General population	Captivity	Attitudes	FA + k-means	Users vs Non-Users (Choice + Captive x Frequency) (8 clusters)
Zhao et al. (2014)	Chicago, IL, USA	Cross-sectional	Transit	Loyalty	Personal	A priori	Captive + Choice
Van Lierop and El-Geneidy (2017)	Montreal and Vancouver, Canada	Repeated Cross-sectional	Transit	Captivity & Satisfaction/ Loyalty	Personal + Attitudes	FA + k-means	Captive + Choice + Captive by choice
Vicente et al. (2020)	Lisbon, Portugal	Cross-sectional	Transit	Loyalty	Personal	A priori	Captive + Choice
Guerra (2022)	Philadelphia, PA, USA	Cross-sectional	Transit + Car	Choice rider	Personal + Behavior + Geography	Logit Model	Captive + Choice
Carvalho and El-Geneidy (2024)	Montreal, Canada	Repeated Cross-sectional	Transit	Satisfaction & Travel Behavior	Attitudes + Behavior	FA + k-means	Captive + Choice + Captive by choice
Mode choice and transit adoption							
Anable (2005)	Manchester, England	Cross-sectional	Car + Alternatives	Mode choice	Attitudes	FA + k-means	Car Ownership x Attitudes (6 clusters)
Cheng et al. (2017)	Fushun, China	Cross-sectional	Low-income commuters	Mode choice	Attitudes	FA + k-means	Mode-related Attitudes (5 clusters)
Mugion et al. (2018)	Rome, Italy	Cross-sectional	Transit + Car	Mode choice	Personal	A priori	Car owner vs non-owner
Dent et al. (2021)	Montreal, Canada	Cross-sectional	General population	Mode choice	Attitudes + Behavior	FA + k-means	LRT adoption (4 clusters)
Alousi-Jones et al. (2025)	Six Canadian Metropolitan Regions	Cross-sectional	Non-Transit Users (Older adults)	Mode choice	Attitudes	FA + k-means + A priori	Transit-related Attitudes (4 clusters)
Balaghi et al. (2026)	Montreal, Canada	Repeated Cross-sectional and Panel	General population	Mode choice	Attitudes + Behavior	FA + k-means	LRT adoption (4 clusters)
Attitudes, Satisfaction and Loyalty							
Tyrinopoulos and Antoniou (2008)	Athens and Thessaloniki, Greece	Cross-sectional	Transit	Satisfaction	Personal	A priori	Male vs Female

(continued on next page)

(*continued*)

Paper	Context	Data	Sample	Clustering Focus	Clustering Variables	Method	**Classification**
Kim and Ulfarsson (2012)	St. Louis, MO, USA	Cross-sectional	Transit	Loyalty	Attitudes	A priori	Committed vs Uncertain
Attitudes, Satisfaction and Loyalty							
Shiftan et al. (2015)	Haifa–Tel Aviv, Israel	Cross-sectional	Transit	Loyalty	Behavior	A priori	Bus vs Rail users
Chen (2016)	Taiwan	Cross-sectional	Transit	Behavioral intention	Geography	A priori	Jurisdiction groups
Fu and Juan (2017)	Shaoxing, China	Cross-sectional	Transit	Loyalty	Attitudes	FA + k-means	Satisfaction vs Intention (4 clusters)
Fu et al. (2018)	Suzhou, China	Cross-sectional	Transit	Loyalty	Personal	A priori	Male vs Female
Grisé and El-Geneidy (2018)	Greater Toronto, Canada	Repeated Cross-sectional	Transit	Satisfaction	Attitudes + Behavior + Geography	FA + k-means	Spatial Travel-Attitudes (7 clusters)
Sun and Duan (2019)	Xiamen, China	Cross-sectional	General population	Loyalty	Attitudes + Behavior	Centroid clustering × a priori	Loyalty-based (4 clusters)
Allen et al. (2019)	Madrid, Spain	Cross-sectional	Transit	Satisfaction/ Loyalty	Personal + Behavior	A priori	Time/Age/Frequency groups
Eldeeb and Mohamed (2020)	Hamilton, Canada	Cross-sectional	Current + Potential Transit Users	Service Quality	Attitudes + Behavior + Personal	Latent class Choice Model	Transit-service priorities (3 clusters)
Mesbah et al. (2022)	Tehran, Iran	Cross-sectional	Transit	Satisfaction	Personal + Behavior	LCC	Transit-service priorities (3 clusters)
Jamal et al. (2023)	Hamilton, Canada	Cross-sectional	General population	Travel Attitudes	Attitudes	LCA	Travel-related attitudes (4 clusters)
Travel Behavior							
Viallard et al. (2019)	Gatineau, Canada	Longitudinal	Transit	Travel Behavior	Behavior	k-means	Weekly travel patterns
Cycling and air transit							
Damant-Sirois et al. (2014)	Montreal, Canada	Cross-sectional	Cyclists	Infrastructure improvement	Attitudes	FA + k-means	Cycling Typology (4 clusters)
Allen et al. (2020)	Calabria, Italy	Cross-sectional	Air Transit	Satisfaction	Attitudes	PCA	Accessory vs Technology users
Goudis et al. (2025)	Montreal, Canada	Cross-sectional	Cyclists	Barriers and Travel Behavior	Attitudes	FA + k-means	Cycling-related preferences and barriers (Riders vs non-Riders) (8 clusters)

Appendix A2. Sociodemographic and behavioral characteristics of pre-implementation market segments

Variable	Transit-Reliant Potential User	Telecommuter Potential Choice Rider	Walkability-Oriented Individual	Car-Oriented Individual	2021 sample
Sample share	**19%**	**23%**	**28%**	**31%**	**100%**
Sociodemographic characteristics					
Gender					
Female	53.30%	50.00%	48.50%	47.80%	49.50%
Male	45.20%	48.20%	47.10%	50.20%	47.90%
Age					
18 to 35	43.70%	31.30%	35.50%	18.90%	31.00%
36 to 64	45.20%	51.20%	49.60%	45.80%	47.90%
65 and over	11.10%	17.50%	15.00%	35.30%	21.00%
Income [in CAD]					
Below 60 k	53.70%	30.90%	61.20%	49.90%	49.40%
60 k-120 k	34.70%	39.70%	31.20%	35.90%	35.20%
Over 120 k	11.60%	29.40%	7.60%	14.20%	15.30%
Employment status					
Worker	64.30%	76.50%	58.20%	51.40%	61.40%
Student	21.60%	9.70%	13.40%	4.80%	11.50%
Retired	19.90%	19.90%	20.80%	38.00%	25.70%
Immigrant	16.40%	17.80%	21.40%	15.30%	17.80%
Household composition					

(continued on next page)

(*continued*)

Variable	Transit-Reliant Potential User	Telecommuter Potential Choice Rider	Walkability-Oriented Individual	Car-Oriented Individual	2021 sample
Household size*	1.9 (1.1)	2.3 (1.1)	1.8 (1.0)	2.1 (1.7)	2.0 (1.3)
Children in the household	9.30%	31.10%	12.30%	15.30%	16.90%
Reported disability	19.60%	10.00%	15.60%	24.10%	17.70%
*Telecommuting frequency [over 7 days] **	0.6 (1.4)	1.5 (1.9)	0.4 (1.1)	0.0 (0.3)	0.6 (1.4)
Access to at least one private automobile [per household]	40.10%	87.80%	32.10%	97.60%	66.30%
Mode Share					
Car share (last 7 days) *	11% (16%)	46% (36%)	8% (19%)	77% (30%)	38% (40%)
Transit share (last 7 days) *	57% (25%)	8% (15%)	5% (11%)	4% (11%)	15% (25%)
Active share (last 7 days) *	32% (24%)	45% (35%)	84% (26%)	17% (27%)	45% (39%)
The Pie-IX BRT corridor					
*Distance to the closest Pie-IX BRT station [in km] **	1.4 (1.0)	1.6 (1.3)	1.8 (1.0)	2.0 (1.4)	1.8 (1.2)
Intention to use	83.00%	78.20%	48.40%	16.90%	52.00%
Main reason for use: I will have a shorter travel time	54.80%	40.20%	31.40%	7.10%	30.40%
Main reason to NOT use: It won't go where I want to go	65.70%	84.50%	78.60%	65.40%	71.40%
Support for the Pie-IX BRT being positive for Greater Montreal	83.90%	95.50%	82.90%	65.00%	80.50%

* *Mean (Standard Deviation).*

Appendix A3. Sociodemographic and behavioral characteristics of post-implementation market segments

Variable	Transit-Reliant BRT Rider	Telecommuter Choice Rider	Walkability-Oriented Individual	Car-Oriented Individual	2023–24 sample
Sample share	**23%**	**16%**	**30%**	**32%**	**100%**
Sociodemographic characteristics					
Gender					
Female	55.60%	49.20%	51.70%	45.30%	50.20%
Male	41.90%	48.00%	45.40%	53.20%	47.50%
Age					
18 to 35	53.00%	31.50%	29.90%	20.60%	32.40%
36 to 64	33.00%	65.00%	47.70%	47.20%	46.90%
65 and over	14.00%	3.50%	22.40%	32.10%	20.70%
Income [in CAD]					
Below 60 k	63.20%	25.50%	61.40%	41.90%	50.00%
60 k-120 k	28.70%	44.20%	29.20%	41.00%	35.20%
Over 120 k	8.10%	30.40%	9.50%	17.10%	14.80%
Employment status					
Worker	61.20%	100.00%	52.10%	50.40%	61.10%
Student	31.80%	3.40%	10.30%	8.70%	13.60%
Retired	15.50%	0.30%	26.40%	32.30%	21.80%
Immigrant	23.60%	22.80%	18.40%	15.20%	19.20%
Household composition					
Household size*	2.3 (1.4)	2.2 (1.1)	1.7 (1.0)	2.3 (1.3)	2.1 (1.2)
Children in the household	26.20%	31.70%	18.30%	26.70%	25.30%
Reported disability	17.20%	10.60%	13.60%	22.40%	16.80%
*Telecommuting frequency [over 7 days] **	0.4 (0.8)	4.3 (1.4)	0.4 (0.8)	0.3 (0.7)	1.0 (1.7)
Access to at least one private automobile [per household]	36.80%	62.70%	17.50%	96.50%	54.10%
Mode Share					
Car share (last 7 days) *	10% (20%)	20% (30%)	0% (10%)	60% (40%)	30% (40%)
Transit share (last 7 days) *	70% (30%)	20% (20%)	20% (20%)	10% (10%)	30% (30%)
Active share (last 7 days) *	20% (20%)	60% (30%)	80% (30%)	30% (30%)	50% (40%)
The Pie-IX BRT corridor					
*Distance to the closest Pie-IX BRT station [in km] **	1.1 (1.0)	1.4 (1.0)	1.5 (0.9)	1.5 (1.2)	1.4 (1.1)
Have used the infrastructure	86.90%	50.90%	59.10%	39.90%	57.90%
Main reason for use: I have a shorter travel time	51.20%	17.00%	23.10%	11.30%	24.70%
Main reason for use: The Pie-IX BRT replaced the public transit service I was using before	35.70%	15.30%	15.60%	7.90%	17.60%
Main reason NOT to use: It doesn't go where I want to go	8.00%	35.60%	28.10%	34.00%	26.70%

(*continued on next page*)

(*continued*)

Variable	Transit-Reliant BRT Rider	Telecommuter Choice Rider	Walkability-Oriented Individual	Car-Oriented Individual	2023–24 sample
Support for the Pie-IX BRT being positive for Greater Montreal	85.10%	84.50%	85.30%	71.60%	80.80%
** Mean (Standard Deviation).*					

Appendix A4. Panel descriptive statistics by baseline cluster (unweighted, pre vs. post)

Variable	Transit-reliant (n = 36)		Telecommuter (n = 62)		Walkability (n = 53)		Car (n = 58)		Overall panel (n = 209)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Gender										
Men	55.6% (n = 20)	55.6% (n = 20)	79.0% (n = 49)	77.4% (n = 48)	62.3% (n = 33)	62.3% (n = 33)	65.5% (n = 38)	69.0% (n = 40)	67.0% (n = 140)	67.5% (n = 141)
Women	44.4% (n = 16)	44.4% (n = 16)	19.4% (n = 12)	19.4% (n = 12)	35.8% (n = 19)	35.8% (n = 19)	29.3% (n = 17)	29.3% (n = 17)	30.6% (n = 64)	30.6% (n = 64)
Other	–	–	1.6% (n = 1)	3.2% (n = 2)	1.9% (n = 1)	1.9% (n = 1)	5.2% (n = 3)	1.7% (n = 1)	2.4% (n = 5)	1.9% (n = 4)
Age										
18–35	25.0% (n = 9)	19.4% (n = 7)	11.3% (n = 7)	9.7% (n = 6)	26.4% (n = 14)	22.6% (n = 12)	10.3% (n = 6)	6.9% (n = 4)	17.2% (n = 36)	13.9% (n = 29)
36–64	63.9% (n = 23)	58.3% (n = 21)	79.0% (n = 49)	74.2% (n = 46)	56.6% (n = 30)	50.9% (n = 27)	60.3% (n = 35)	56.9% (n = 33)	65.6% (n = 137)	60.8% (n = 127)
65 and over	11.1% (n = 4)	22.2% (n = 8)	9.7% (n = 6)	16.1% (n = 10)	17.0% (n = 9)	26.4% (n = 14)	29.3% (n = 17)	36.2% (n = 21)	17.2% (n = 36)	25.4% (n = 53)
Household income										
Low income	38.9% (n = 14)	33.3% (n = 12)	12.9% (n = 8)	12.9% (n = 8)	41.5% (n = 22)	35.8% (n = 19)	34.5% (n = 20)	34.5% (n = 20)	30.6% (n = 64)	28.2% (n = 59)
Middle income	44.4% (n = 16)	50.0% (n = 18)	33.9% (n = 21)	22.6% (n = 14)	37.7% (n = 20)	30.2% (n = 16)	39.7% (n = 23)	39.7% (n = 23)	38.3% (n = 80)	34.0% (n = 71)
High income	16.7% (n = 6)	16.7% (n = 6)	53.2% (n = 33)	64.5% (n = 40)	20.8% (n = 11)	34.0% (n = 18)	25.9% (n = 15)	25.9% (n = 15)	31.1% (n = 65)	37.8% (n = 79)
Employment status										
Worker	66.7% (n = 24)	63.9% (n = 23)	85.5% (n = 53)	80.6% (n = 50)	67.9% (n = 36)	67.9% (n = 36)	56.9% (n = 33)	53.4% (n = 31)	69.9% (n = 146)	67.0% (n = 140)
Student	8.3% (n = 3)	5.6% (n = 2)	1.6% (n = 1)	–	3.8% (n = 2)	–	1.7% (n = 1)	1.7% (n = 1)	3.3% (n = 7)	1.4% (n = 3)
Retired	22.2% (n = 8)	30.6% (n = 11)	14.5% (n = 9)	14.5% (n = 9)	24.5% (n = 13)	26.4% (n = 14)	36.2% (n = 21)	37.9% (n = 22)	24.4% (n = 51)	26.8% (n = 56)
Immigrant	25.0% (n = 9)	22.2% (n = 8)	9.7% (n = 6)	9.7% (n = 6)	20.8% (n = 11)	20.8% (n = 11)	10.3% (n = 6)	10.3% (n = 6)	15.3% (n = 32)	14.8% (n = 31)
Household composition										
Household size	1.89 (1.21)	2.00 (1.12)	2.58 (1.25)	2.58 (1.34)	2.06 (1.20)	2.04 (1.21)	1.91 (1.00)	1.88 (0.96)	2.14 (1.19)	2.15 (1.20)
Children in household	11.1% (n = 4)	13.9% (n = 5)	41.9% (n = 26)	41.9% (n = 26)	20.8% (n = 11)	20.8% (n = 11)	12.1% (n = 7)	15.5% (n = 9)	23.0% (n = 48)	24.4% (n = 51)
Reported disability	13.9% (n = 5)	11.1% (n = 4)	6.5% (n = 4)	6.5% (n = 4)	17.0% (n = 9)	15.1% (n = 8)	20.7% (n = 12)	24.1% (n = 14)	14.4% (n = 30)	14.4% (n = 30)
Telecommuting frequency	0.64 (1.44)	0.97 (1.80)	2.02 (2.06)	1.84 (1.99)	0.32 (1.05)	1.30 (1.84)	0.09 (0.39)	0.83 (1.60)	0.81 (1.60)	1.27 (1.85)
Car access (1 or more)	41.7% (n = 15)	44.4% (n = 16)	80.6% (n = 50)	80.6% (n = 50)	30.2% (n = 16)	32.1% (n = 17)	100.0% (n = 58)	94.8% (n = 55)	66.5% (n = 139)	66.0% (n = 138)
Mode share										
Car share (last 7 days)	11% (15%)	18% (29%)	49% (39%)	35% (34%)	9% (19%)	7% (16%)	74% (29%)	68% (37%)	39% (39%)	34% (39%)
Transit share (last 7 days)	50% (28%)	39% (34%)	8% (14%)	12% (24%)	5% (10%)	8% (20%)	3% (11%)	4% (13%)	13% (23%)	13% (26%)
Active share (last 7 days)	39% (30%)	44% (34%)	43% (38%)	54% (35%)	86% (22%)	83% (27%)	21% (27%)	28% (33%)	47% (39%)	52% (38%)
Pie-IX BRT Corridor										
Distance to BRT (km)	1.43 (0.96)	1.42 (0.95)	1.54 (0.95)	1.57 (0.98)	2.02 (0.92)	1.99 (0.93)	1.96 (1.42)	1.96 (1.42)	1.76 (1.11)	1.76 (1.12)
Intention to use BRT	91.7% (n = 33)	–	72.6% (n = 45)	–	41.5% (n = 22)	–	17.2% (n = 10)	–	52.6% (n = 110)	–
Used BRT	–	66.7% (n = 24)	–	46.8% (n = 29)	–	41.5% (n = 22)	–	20.7% (n = 12)	–	41.6% (n = 87)

Note: % (n) for categorical variables; mean (SD) for numeric variables. Panel sample n = 209.

Data availability

The data that has been used is confidential.

References

Ajzen, I., 1985. From intentions to actions: A theory of planned behavior. Action Control: From Cognitions to Behavior, 11–39.
Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.
Ajzen, I., 2011. The theory of planned behaviour: reactions and reflections. Psychol. Health 26 (9), 1113–1127.
Allen, J., Bellizzi, M.G., Eboli, L., Forciniti, C., Mazzulla, G., 2020. Service quality in a mid-sized air terminal: a SEM-MIMIC ordinal probit accounting for travel, sociodemographic, and user-type heterogeneity. J. Air Transp. Manag. 84, 101780.
Allen, J., Eboli, L., Forciniti, C., Mazzulla, G., Ortuzar, J., 2019. The role of critical incidents and involvement in transit satisfaction and loyalty. Transp. Policy 75, 57–69.
Allen, J., Farber, S., 2020a. Planning transport for social inclusion: an accessibility-activity participation approach. Transp. Res. Part D: Transp. Environ. 78. https://doi.org/10.1016/j.trd.2019.102212.
Allen, J., Farber, S., 2020b. Suburbanization of transport poverty. Ann. Am. Assoc. Geogr. 111 (6), 1833–1850.
Alousi-Jones, M., Carvalho, T., Zhang, M., Jimenez, I., El-Geneidy, A., 2025. Who is willing to take transit in the future? Older adults' perceived challenges and barriers to using public transit across Canada. Transp. Res. A Policy Pract. 192, 104376.
Anable, J., 2005. 'Complacent car addicts' or 'aspiring environmentalists'? Identifying travel behaviour segments using attitude theory. Transp. Policy 12 (1), 65–78.
Balaghi, S., Carvalho, T., Victoriano-Habit, R., El-Geneidy, A., 2026. Changes in the public transit market following the introduction of a new light rail system: a before-and-after study in Montreal, Canada. J. Urban Mob. 9, 100178.
Bamberg, S., Schmidt, P., 2003. Incentives, morality, or habit? Predicting students' car use for University routes with the models of Ajzen, Schwartz, and Triandis. Environ. Behav. 35 (2), 264–285.
Beimborn, E., Greenwald, M., Jin, X., 2003. Accessibility, connectivity, and captivity: Impacts on transit choice. Transport. Res. Record: J. Transport. Res. Board 1835 (03), 1–9.
Cain, A., Flynn, J., 2013. Examining the ridership attraction potential of bus rapid transit: a quantitative analysis of image and perception. J. Public Transp. 16 (4), 63–82.
Carvalho, T., El-Geneidy, A., 2024. Everything has changed: the impacts of the COVID-19 pandemic on the transit market in Montréal, Canada. Transportation.
Carvalho, T., Romano, C., Gadda, T., 2022. Loyalty and public transit: a quantitative systematic review of the literature [Web]. Transp. Rev. 42 (3), 362–383.
Cervero, R., Murakami, J., Miller, M., 2010. Direct ridership model of bus rapid transit in Los Angeles County, California. Transport. Res. Record 2145 (1), 1–7.
Chen, C., Chao, W., 2011. Habitual or reasoned? Using the theory of planned behavior, technology acceptance model, and habit to examine switching intentions toward public transit. Transport. Res. F: Traffic Psychol. Behav. 14 (2), 128–137.
Chen, H., 2016. Structural interrelationships of group service quality, customer satisfaction, and behavioral intention for bus passengers. Int. J. Sustain. Transp. 10 (5), 418–429.
Cheng, L., Chen, X., Lam, W., Yang, S., Lei, D., 2017. Public transit market research of low-income commuters using attitude-based market segmentation approach: Case study of fushun, China. Transp. Res. Rec. 2671, 10–19.
Currie, G., 2005. The demand performance of bus rapid transit. J. Public Transp. 8 (1), 41–55.
Currie, G., Delbosc, A., 2011. Understanding bus rapid transit route ridership drivers: an empirical study of Australian BRT systems. Transp. Policy 18 (5), 755–764.
Currie, G., Delbosc, A., 2014. Assessing bus rapid transit system performance in Australasia. Res. Transp. Econ. 48, 142–151.
Damant-Sirois, G., Grimsrud, M., El-Geneidy, A., 2014. What's your type: a multidimensional cyclist typology. Transportation 41 (6), 1153–1169.
DeBell, M., Krosnick, J. A., 2009. Computing weights for American National Election Study survey data (ANES Technical Report series, no. nes012427, Issue. http://www.electionstudies.org.
Deng, T., Nelson, J., 2011. Recent developments in bus rapid transit: a review of the literature. Transp. Rev. 31 (1), 69–96.
Deng, T., Nelson, J., 2012. The perception of bus rapid transit: a passenger survey from Beijing Southern Axis BRT Line 1. Transp. Plan. Technol. 35 (2), 201–219.
Dent, N., Hawa, L., DeWeese, J., Wasfi, R., Kestens, Y., El-Geneidy, A., 2021. Market-segmentation study of future and potential users of the new Réseau Express Métropolitain light rail in Montreal, Canada. Transport. Res. Record 2675 (10), 1043–1054.
Diana, M., Mokhtarian, P.L., 2009. Grouping travelers on the basis of their different car and transit levels of use. Transportation 36 (4), 455–467.
Dillman, D., Smyth, J., Christian, L., 2014. Internet, phone, mail, and mixed-mode surveys: the tailored design method, (4th ed.). Wiley.
El-Geneidy, A., Levinson, D., Diab, E., Boisjoly, G., Verbich, D., Loong, C., 2016. The cost of equity: Assessing transit accessibility and social disparity using total travel cost. Transp. Res. A Policy Pract. 91, 302–316.
Eldeeb, G., Mohamed, M., 2020. Quantifying preference heterogeneity in transit service desired quality using a latent class choice model. Transp. Res. A Policy Pract. 139, 119–133.
Ernst, J., 2005. Initiating bus rapid transit in Jakarta, Indonesia. Transp. Res. Rec. 1903 (1), 20–26.
Friedrichsmeier, T., Matthies, E., Klöckner, C.A., 2012. Explaining stability in travel mode choice: an empirical comparison of two concepts of habit. Transport. Res. F: Traffic Psychol. Behav. 16, 1–13.
Fu, X., Juan, Z., 2017. Drivers of transit service loyalty considering heterogeneity between user segments. Transp. Plan. Technol. 40 (5), 611–623.
Fu, X., Zhang, J., Chan, F., 2018. Determinants of loyalty to public transit: a model integrating Satisfaction-loyalty theory and expectation-confirmation theory [article]. Transp. Res. A Policy Pract. 113, 476–490.
Fujii, S., Gärling, T., Kitamura, R., 2001. Changes in drivers' perceptions and use of public transport during a freeway closure: Effects of temporary structural change on cooperation in a real-life social dilemma. Environ. Behav.
Gardner, B., 2009. Modelling motivation and habit in stable travel mode contexts. Transport. Res. F: Traffic Psychol. Behav. 12 (1), 68–76.
Gärling, T., Axhausen, K.W., 2003. Introduction: Habitual travel choice. Transportation 30 (1), 1–11.
Gärling, T., Garvill, J., 1993. Psychological explanations of participation in everyday activities. Adv. Psychol.
Gärling, T., Schuitema, G., 2007. Travel demand management targeting reduced private car use: Effectiveness, public acceptability and political feasibility. J. Soc. Issues.
P. Goudis R. Victoriano-Habit T. Carvalho A. El-Geneidy Goudis, P., Victoriano-Habit, R., Carvalho, T., & El-Geneidy, A., 2025. Barriers, Adoption, and Use of a Bike-Sharing System: A Market-Segment Approach to Current and Potential Users in Montréal, Canada. Transportation Research Record, 03611981251340377.
Grisé, E., El-Geneidy, A., 2018. Where is the happy transit rider? Evaluating satisfaction with regional rail service using a spatial segmentation approach. Transp. Res. A Policy Pract. 114, 84–96.
Guerra, E., 2022. What the heck is a choice rider? A theoretical framework and empirical model. J. Transp. Land Use 15 (1).
Hair, J., Black, W., Babin, B., Anderson, R., 2014. Multivariate data analysis, (7 ed.). Prentice Hall.
Hensher, D., Li, Z., Mulley, C., 2014. Drivers of bus rapid transit systems–Influences on patronage and service frequency. Res. Transp. Econ. 48, 159–165.
Ibraeva, A., Correia, G., Silva, C., Antunes, A., 2022. Mobility impacts of a new metro system with transit-oriented development features. Transp. Res. Part D: Transp. Environ. 109, 103357.
Ibraeva, A., Correia, G., Silva, C., Antunes, A., 2023. Impacts of transit-oriented development on car use over a 10-year period in Porto, Portugal: from macro-to micro-analysis. Int. J. Sustain. Transp. 17 (11), 1195–1206.
Jamal, S., Newbold, K. B., Scott, D. M., 2023. Developing a typology of daily travelers based on transportation attitudes: Application of latent class analysis using a survey of millennials and older adults in Hamilton, Ontario. Growth and Change.

Kim, S., Ulfarsson, G., 2012. Commitment to light rail transit patronage: Case study for St. Louis MetroLink. J. Urban Plann. Develop.-Asce 138 (3), 227–234.
Krizek, K., El-Geneidy, A., 2007. Segmenting preferences and habits of transit users and non-users. J. Public Transp. 10 (3), 71–94.
Levinson, H., Zimmerman, S., Clinger, J., Gast, J., 2003. Bus rapid transit: Synthesis of case studies. Transp. Res. Rec. 1841 (1), 1–11.
Mattioli, G., Lucas, K., Marsden, G., 2017. Transport poverty and fuel poverty in the UK: from analogy to comparison. Transp. Policy 59, 93–105.
McCarthy, L., Delbosc, A., Currie, G., Molloy, A., 2017. Factors influencing travel mode choice among families with young children (aged 0–4): a review of the literature. Transp. Rev. 37 (6), 767–781.
Mesbah, M., Sahraei, M., Soltanpour, A., Habibian, M., 2022. Perceived service quality based on passenger and trip characteristics: a structural equation modeling approach. J. Rail Transport Plan. Manage. 23.
Müggenburg, H., Busch-Geertsema, A., Lanzendorf, M., 2015. Mobility biographies: a review of achievements and challenges of the mobility biographies approach and a framework for further research. J. Transp. Geogr. 46, 151–163.
Mugion, R., Toni, M., Raharjo, H., Di Pietro, L., Sebathu, S., 2018. Does the service quality of urban public transport enhance sustainable mobility? J. Clean. Prod. 174, 1566–1587.
Nolte, K., Schaefer, K., 2024. Widening the gap? Evidence from Germany for changes in the attitude behaviour gap for transportation during COVID-19. J. Transp. Geogr. 118, 103940.
Oort, N., MennoYap, 2021. Chapter Six - Innovations in the appraisal of public transport projects. In Advances in Transport Policy and Planning (pp. 127-164). Academic Press.
Pasek, J., 2018. anesrake: ANES Raking Implementation. R package version 0.80. https://CRAN.R-project.org/package=anesrake.
Ravensbergen, L., Fournier, J., El-Geneidy, A., 2023. Exploratory analysis of mobility of care in Montreal, Canada. Transport. Res. Record 2677 (1), 1499–1509.
Rodriguez, D., Vergel-Tovar, C., 2018. Urban development around bus rapid transit stops in seven cities in Latin-America. J. Urban.: Int. Res. Placemaking Urban Sustain. 11 (2), 175–201.
Schwanen, T., Banister, D., Anable, J., 2012. Rethinking habits and their role in behaviour change: the case of low-carbon mobility. J. Transp. Geogr. 24, 522–532.
Sheppard, B.H., Hartwick, J., Warshaw, P.R., 2002. The theory of reasoned action: a meta-analysis of past research with recommendations for modifications and future research. J. Consum. Res.
Shiftan, Y., Barlach, Y., Shefer, D., 2015. Measuring passenger loyalty to public transport modes [Article]. J. Public Transp. 18 (1), 16.
StatCan, 2016. Census Profile, 2016 Census: Montréal [Census metropolitan area], Quebec and Quebec [Province]. Retrieved 23/11/2022 from https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/page.cfm?Lang=E&Geo1=CMACA&Code1=462&Geo2=PR&Code2=24&Data=Count&SearchText=Montreal&SearchType=Begins&SearchPR=01&B1=Journey%20to%20work&TABID=1.
StatCan, 2021. Census Profile, 2021 Census. Retrieved 23/05/2023 from https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/index.cfm?Lang=E.
Statistics Canada, 2023. 2021 Census of Population. Statistics Canada Catalogue no. 98-316-X2021001. Retrieved May 24, 2023 from https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/index.cfm?Lang=E.
Stewart, O., Moudon, A., Saelens, B., 2017. The causal effect of Bus Rapid Transit on changes in transit ridership. J. Public. Trans. 20 (1), 91–103.
Sun, S., Duan, Z., August 2019. Modeling passengers' loyalty to public transit in a two-dimensional framework: a case study in Xiamen, China. Transport. Res. Part A: Policy Pract. 124, 295–309.
Thøgersen, J., 2006. Understanding repetitive travel mode choices in a stable context: a panel study approach. Transport. Res. Part A: Policy Pract. 40 (8), 621–638.
Tyrinopoulos, Y., Antoniou, C., 2008. Public transit user satisfaction: Variability and policy implications. Transport Policy 15 (4), 260–272.
Van Lierop, D., El-Geneidy, A., 2017. A new market segmentation approach: evidence from two Canadian Cities. J. Public Transport. 20 (1), 20–43.
Vergel-Tovar, C., Rodriguez, D., 2018. The ridership performance of the built environment for BRT systems: evidence from Latin America. J. Transport Geogr. 73, 172–184.
Verplanken, B., Aarts, H., Van Knippenberg, A., 2002. Habit, information acquisition, and the process of making travel mode choices. Europ. J. Soc. Psychol.
Viallard, A., Trépanier, M., Morency, C., 2019. Assessing the evolution of transit user behavior from smart card data. Transport. Res. Rec. 2673 (4), 184–194.
Vicente, P., Sampaio, A., Reis, E., 2020. Factors influencing passenger loyalty towards public transport services: does public transport providers' commitment to environmental sustainability matter? Case Stud. Transport Policy 8 (2), 627–638.
Victoriano-Habit, R., Negm, H., James, M., Goudis, P., & El-Geneidy, A., 2024. Measuring the impacts of the Réseau express métropolitain (REM): Progress Report 2019-2023.
von Bergmann, J., Shkolnik, D., Jacobs, A., 2021. cancensus: R package to access, retrieve, and work with Canadian Census data and geography. R package version 0.4.2. https://mountainmath.github.io/cancensus/.
Wilson, F.R., Stevens, A.M., Robinson, J.B., 1984. Identifying mode choice constrained urban travel market segments. Cana. J. Civ. Eng. 11 (4), 924–932.
Zhao, J., Webb, V., Shah, P., 2014. Customer loyalty differences between captive and choice transit riders. Transport. Res. Record: J. Transport. Res. Board 2415 (1), 80–88.
Zwick, W., Velicer, W., 1986. Comparison of five rules for determining the number of components to retain. Psychol. Bull. 99 (3), 432–442.