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Changes in the public transit market following the introduction of a new light rail system: A before-and-after study in Montreal, Canada

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ABSTRACT

The introduction of large-scale public transit infrastructure often carries the promise of improving regional mobility, reducing car dependency, and fostering sustainable urban development. However, the success of such investments depends not only on the quality of service delivered but also on how different segments of the population respond to the new mobility option. This study explores the impacts of a major infrastructure project, Réseau express métropolitain (REM) in Montréal, on the public transit market. The REM is a 67-km automated light rail system designed to enhance regional mobility in Montréal, Canada with an investment of more than $9 Billion CAD. We draw on cross-sectional and longitudinal data from the Montréal Mobility Survey in 2022 (before REM operations) and 2024 (after the opening of the South Shore branch). We apply exploratory factor analysis and weighted k-means clustering to identify and track transit user segments over time. Across both waves, a four-cluster solution emerged indicating that the overall market structure remained stable. However, longitudinal analysis revealed significant individual transitions, with many potential REM telecommuters reverting to car-oriented behaviors. These findings highlight the duality of stable market profiles but fluid individual behaviors, demonstrating that new infrastructure can reshape travel patterns within existing markets rather than creating entirely new ones. These findings are of interest to policymakers and transit planners interested in market segmentation to understand behavioral adaptation regarding new LRT infrastructures over time.

1. Introduction

Light rail transit (LRT) investments are frequently promoted as catalysts for sustainable mobility, urban growth, and improved accessibility (Currie & Delbosc, 2013; Ramos-Santiago & Brown, 2016). By enhancing connectivity and offering high-capacity, reliable service, LRT systems are expected to reduce automobile dependence and attract new riders (Kepaptsoglou et al., 2017). Beyond mobility outcomes, LRT systems are often associated with neighborhood change and concerns about gentrification (Padeiro et al., 2019). While evidence is mixed and context dependent (Baker & Lee, 2019; Chava & Renne, 2022), such processes underscore the importance of ensuring that accessibility improvements benefit diverse rider groups. Therefore, understanding who uses, intends to use, or refrains from using new systems is critical to evaluating their broader impacts. The lessons from such projects extend well beyond individual case studies as understanding which groups adopt new systems, and which remain excluded, is essential for planners and policymakers worldwide.

Understanding the impacts of new LRT infrastructure requires not only assessing aggregate ridership but also examining the heterogeneity of user responses (Anable, 2005; Diana & Mokhtarian, 2009). To capture this diversity, transport researchers have increasingly applied market segmentation techniques, which divide the overall travel market into more homogeneous groups, or segments, of users and non-users who share similar socio-demographic, attitudinal, or behavioral characteristics (Allen et al., 2019; Eldeeb & Mohamed, 2020; Fu & Juan, 2017; Kim & Ulfarsson, 2012; Mesbah et al., 2022; Viallard et al., 2019; Wang et al., 2022). Within this context, potential markets refer to groups that are not currently using transit but display characteristics or attitudes suggesting they could be attracted under the right conditions, such as improved service and access to transit. Segmentation studies have offered valuable insights for planning, such as tailoring service

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improvements, designing marketing strategies, and identifying latent demand (Pan & Ryan, 2023). However, most of this work remains static, relying on cross-sectional data collected either before or after system implementation.

This limitation is critical, as pre-launch expectations do not always translate into post-launch behaviors. Evidence on how individuals' intentions to use new infrastructure align with their actual ridership once it becomes operational remains scarce. For instance, Dent et al. (2021) provided important insights by segmenting potential users of Montréal's Réseau express métropolitain (REM) prior to its launch, identifying socio-economic and attitudinal groups most likely to adopt the system. Yet, like most segmentation studies, their analysis offered only a snapshot in time, leaving open questions about the stability of market profiles and the alignment between stated intentions and revealed behaviors once operations begin.

This paper addresses this gap by examining how rider markets evolve before and after the launch of the REM, a fully automated light rail system that will span 67 km once completed. Our analysis focuses on the system's first operational branch, which opened in late July 2023, connecting Montréal's South Shore to the downtown core. Drawing on two waves of the Montréal Mobility Survey (2022, pre-launch, $N = 623$; and 2024, post-launch, $N = 1645$, with a panel subsample of $N = 175$), we apply exploratory factor analysis and weighted k-means clustering to identify market profiles, assess their stability, and track individual transitions over time.

By leveraging both repeated cross-sectional and longitudinal samples, the study provides rare evidence on the dynamics of transit markets in the context of the introduction of major LRT infrastructure. Specifically, the study addresses three research questions: (i) To what extent do user profiles remain stable over time, and how do their defining characteristics evolve as the new infrastructure becomes operational? (ii) How do individuals transition between user segments over time, particularly with the opening of the REM? and (iii) How do respondents stated intentions to use the REM (pre-launch) align with their actual ridership behaviors once the system becomes operational? In answering these questions, the paper provides insights for transit planning and policymaking aimed at maximizing the benefits of new public transit infrastructure. In doing so, the paper contributes to the literature by (i) advancing segmentation research through a longitudinal framework, (ii) offering transferable insights for transit planning and policymaking in diverse contexts, and (iii) providing a systematic examination of intention–behavior gaps in LRT adoption.

2. Literature review

To situate this study, the literature review first outlines the determinants of LRT ridership, then examines how market segmentation frameworks have been used to capture user heterogeneity and finally highlights the limited evidence on how markets evolve following the implementation of new LRT infrastructure.

2.1. The determinants of LRT ridership

Light rail transit corridors are frequently shown to function as catalysts for behavioral change. For example, in their study of the Hiawatha corridor in Minneapolis, Cao and Ermagun (2017) employed a quasi-longitudinal survey of 597 residents who relocated after the line opened. Their findings reveal that the corridor functions both as a catalyst, improving transit accessibility and encouraging greater transit use with reduced driving, and as a magnet, attracting residents already predisposed to transit use. Similarly, in Cyprus, Kepaptsoglou et al. (2017) derived a direct demand model using stated-preference surveys and traffic demand data, estimating that a proposed LRT would attract approximately 23,000 daily passengers, shifting around 3.5 % of car trips.

Several system-level attributes have been consistently linked to higher ridership, including vehicle speed and capacity, quality of service, employment density, and integrated ticketing (Currie & Delbosc, 2013; Ramos-Santiago & Brown, 2016). In their analysis of nine U.S. cities, Kuby et al. (2004) found that boardings at LRT stations increase with higher nearby employment and residential density, stronger bus connectivity, more park-and-ride spaces, and larger shares of renter households. Kim et al. (2007) added further nuance in their study of St. Louis' Metro Link, showing that ridership is shaped not only by individual and built environment characteristics but also by crime and safety concerns. The study underscores that increasing ridership requires treating LRT stations as multimodal hubs, improving bus integration, pedestrian accessibility, and station safety to better support diverse access patterns. In the Montreal context, James et al. (2024) highlighted that social acceptability during the construction phase can play a critical role in eventual ridership. They emphasized the need to mitigate disruptions, ensure safety in construction zones, and foster transparent, inclusive decision-making to sustain long-term public support.

Together, these studies show that LRT ridership is shaped by a complex interplay of land use, service design, network integration, and user perceptions. Yet, while this literature provides valuable insights into the drivers of aggregate ridership trends, it often overlooks the heterogeneity of individual responses and the attitudinal dynamics underlying travel behavior. To address these gaps, many researchers have turned to market segmentation techniques, which allow for the identification of distinct user profiles based on travel preferences, attitudes, and behaviors (Anable, 2005; Diana & Mokhtarian, 2009).

More recently, the COVID-19 pandemic has further transformed transit behavior, producing sharp declines in ridership, increased telecommuting, and shifting travel purposes (Carvalho & El-Geneidy, 2024; Palm et al., 2022). Disadvantaged users remained more reliant on transit, while many choice riders adapted through remote work or shifted to alternative modes (Brough et al., 2021; Haider & Anwar, 2022). Although most evidence speaks to transit systems more broadly rather than LRT specifically, these disruptions provide important context for interpreting current ridership patterns. They highlight the need to monitor how rider segments evolve over time as habits, constraints, and preferences continue to change in light of the pandemic.

2.2. Market segmentation in public transit

Market segmentation has become a widely used framework in public transport planning to account for the heterogeneity of users. One of the earliest distinctions separated captive riders, who rely on transit due to economic or physical constraints, from choice riders, who use transit despite having alternatives, often for reasons of convenience or values (Beimborn et al., 2003; Zhao et al., 2014). While influential, this binary framework has been critiqued as overly simplistic. To address this, Van Lierop and El-Geneidy (2017) introduced a third category, the captive-by-choice riders. This category includes those who could rely on other modes, such as a car, but intentionally depend on transit as their primary mode. They differ from choice riders in that their preference results in consistent dependence on transit, not just selective adoption.

Building on these foundational market classifications, scholars have adopted more nuanced, data-driven approaches that incorporate personal, attitudinal, behavioral, and geographic variables (Allen et al., 2019; Eldeeb & Mohamed, 2020; Fu & Juan, 2017; Kim & Ulfarsson, 2012; Mesbah et al., 2022; Viallard et al., 2019; Wang et al., 2022). Common techniques include factor analysis and k-means clustering, which group users by shared patterns in attitudes, behaviors, and socio-demographic traits (Alousi-Jones et al., 2025; Damant-Sirois & El-Geneidy, 2015; Damant-Sirois et al., 2014; Dent et al., 2021; Grise & El-Geneidy, 2018; Van Lierop & El-Geneidy, 2017). For instance, Jacques et al. (2013) identified segments of Montreal transit users based on trip satisfaction and travel time, while Grise and El-Geneidy (2018) clustered riders according to level of service, loyalty behavior and accessibility. Geographic segmentation has been applied to highlight disparities in access and service perceptions (Grise & El-Geneidy, 2018). Segmenting users and non-users into distinct market groups provides a nuanced foundation for both planning and policy implications, especially in contexts where the emergence of a new transit infrastructure, demographic shifts, and social equity concerns intersect (Pan & Ryan, 2023).

Such segmentation frameworks are particularly useful not only in describing existing markets but in identifying potential or latent demand. In Montréal, Jacques et al. (2013) demonstrated how preferences for operational and hedonic performance vary across groups, offering insights for targeted service adjustments. Dent et al. (2021) extended this line of work by anticipating REM user markets prior to launch, defining distinct rider profiles based on socio-economic and attitudinal indicators, a contribution that this paper builds upon. These studies build on earlier work distinguishing users and non-users (Krizek & El-Geneidy, 2007), contributing to strategies that attract new riders while retaining existing ones.

2.3. Capturing market dynamics before and after new LRT infrastructure

Although segmentation has advanced the understanding of user heterogeneity, most studies continue to rely on cross-sectional data, offering only a static view of attitudes and behaviors at a single point in time. Such approaches limit the ability to capture how markets evolve, particularly in response to major interventions like the introduction of new infrastructure. The distinction is important, as intentions do not always translate into behavior. As Anable (2005) argues, similar behaviors may arise from different motivations, and conversely, similar attitudes may produce divergent outcomes.

Although previous research has explored market segmentation of LRT markets, most studies have focused on either pre-launch expectations (Dent et al., 2021) or post-launch behavior in isolation, typically relying on cross-sectional data (Cao & Schoner, 2014; Kim & Ulfarsson, 2012). As a result, evidence on how individuals stated intentions to use a new system align with their actual behavior once it becomes operational remains limited. Dent et al. (2021), for example, conducted an intention-based segmentation before the launch of Montréal's REM, identifying four distinct clusters (i.e., car-friendly non-users, urban core potential users, transit-friendly users, and leisure and airport users). Their study provided valuable insights into the socio-economic and attitudinal profiles most likely to adopt the REM, highlighting factors such as positive perceptions of neighborhood benefits, proximity to the line, and interest in leisure or airport travel as key drivers of anticipated use. However, because this work was conducted prior to the system's opening, it does not follow up to assess whether these anticipated behaviors ultimately materialized, leaving open questions about the stability of such profiles and the alignment between intentions and revealed travel behavior.

The lack of longitudinal evidence leaves open important issues for both planning and evaluation. In particular, little is known about whether market profiles identified before implementation persist once a system becomes operational, how individuals move between segments in response to new LRT infrastructure, and whether intentions expressed prior to launch reflect in actual ridership. By combining factor and cluster analysis with repeated cross-sectional and longitudinal data, this study addresses these issues, examining both market stability and the alignment between stated and revealed behavior. This approach enables a richer understanding of how rider profiles evolve and how different groups adapt in response to new LRT infrastructure over time.

3. Case study

This study focuses on the first operational branch of the Réseau express métropolitain (REM), a fully automated light rail system under development in the Greater Montréal. The South Shore branch, which connects suburban communities on the South Shore with downtown Montréal, began service in late July 2023. Initial ridership was projected at approximately 30,000 daily passengers (CDPQ Infra, 2017; Wanek-Libman, 2023), but early counts averaged closer to 24,000 (CBC News, 2024). Train frequency ranges from every 4 min during peak hours to every seven minutes during off-peak hours, operating for 20 h a day. Since its launch, the line has experienced recurring disruptions, both operational and weather-related, which have raised concerns about its perceived reliability (CBC News, 2025).

The South Shore branch is the first phase of the broader REM project, a 67-km, $9.4 billion CAD network that will eventually include three branches and serve 190,000 riders daily once fully operational, illustrated in Fig. 1. The remaining branches are scheduled to open between Fall 2025 and Spring 2026, with the final extension to Montréal–Trudeau International Airport expected by 2027. The project is managed and operated by CDPQ Infra, the infrastructure subsidiary of Quebec's public pension fund, under the jurisdiction of the regional transit authority (ARTM). This setting provides a valuable opportunity to explore how stated intentions align with revealed behavior and how rider markets evolve during the early years of a new LRT system.

4. Data sources

This study draws on the Montréal Mobility Survey (MMS), a multi-wave, bilingual, online longitudinal survey administered by the Transportation Research at McGill (TRAM) group across the Greater Montréal region. The MMS was designed to capture perceptions and intentions toward new transit infrastructure, including the REM, alongside information on personal characteristics, travel behavior, transit perceptions, and travel preferences. With more than 300 questions, where respondents answer tailored subsamples depending on their knowledge of the REM, employment status, and proximity to construction, the MMS provides a rich dataset to examine changes in transit markets over time.

To recruit participants, the survey employed multiple strategies across waves, including marketing company advertisement, social media ads, flyer distribution, and personalized email invitations, following best practices outlined by Dillman et al. (2014). Each wave included both new participants and respondents from previous waves, resulting in a sample that combines cross-sectional (one-time) observations with panel (repeated) observations. Consistent data-cleaning protocols were applied across all waves, including the exclusion of responses with very short completion times (fastest 5 %), duplicate entries, implausible age or height differences between waves, incomplete answers, and geolocation outside the Montréal metropolitan area. It is important to note that we observed that the number of filtered responses due to repeated IP addresses constitutes a small fraction of the dataset (5.4 % for 2022 and 4.7 % for 2024). Furthermore, over 80 % of repeated IP responses had five or fewer occurrences, with the maximum repetition being 12. Further detail on the survey instrument and cleaning procedures is available in Victoriano-Habit et al. (2024).

This study focuses on respondents residing within specific spatial boundaries, shown in Fig. 2. These boundaries were delineated to capture individuals with realistic access to the new REM infrastructure and a plausible likelihood of incorporating it into their travel routines. The study area includes the entire South Shore of Montréal, where the REM's first operational segment is currently in service; a 2 km buffer around Gare Centrale station on the island of Montréal, representing a reasonable catchment for REM access; and Nun's Island, whose small geographic size and proximity to its REM station suggest a strong likelihood of use.

Our analysis draws on two key MMS waves: Wave 3 (2022), the most recent pre-launch survey, and Wave 5 (2024), the first post-launch survey. Wave 3 captures baseline travel behavior, intended REM use, and project perceptions prior to opening, while Wave 5 reflects actual ridership and travel patterns one year after the South Shore branch became operational. Within the study area, 623 valid responses were retained in 2022 and 1645 in 2024. A longitudinal subsample of 175

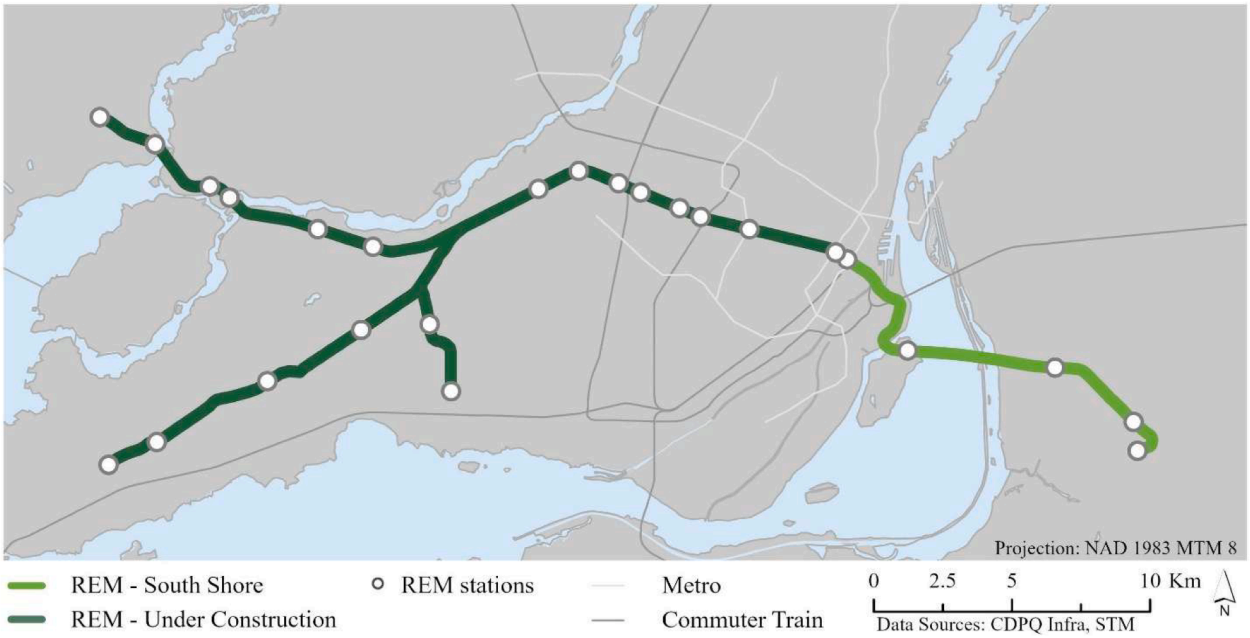

Fig. 1. The Réseau express métropolitain (REM).

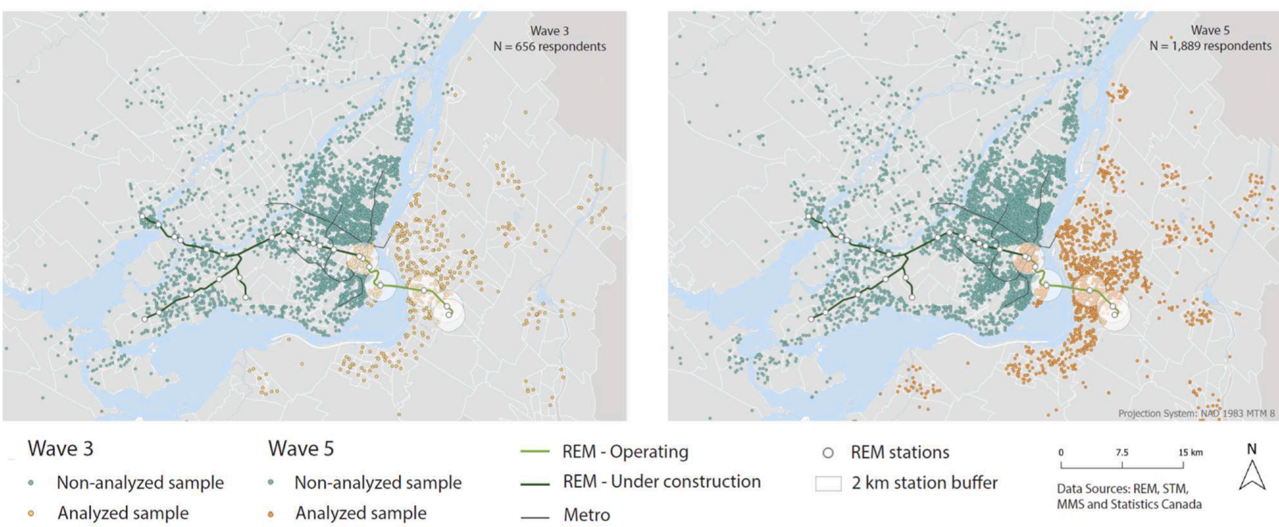

Fig. 2. Respondents in the cross-sectional survey samples (2022: $N = 623$; 2024: $N = 1645$).

respondents completed both waves, allowing for direct comparisons between pre-launch intentions and post-launch behavior.

All analyses rely on weighted data to ensure 2021 Canadian census sociodemographic representativeness of the study area population. Weights were calculated separately for each wave and the panel sample, using the *anesrake* R package (Pasek, 2018), which follows an iterative raking process (DeBell & Krosnick, 2009). The weights were calculated to match the census-tract information of age, income, gender, and mode share obtained from Statistics Canada 2021 census (Statistics Canada, 2023), which was retrieved through the cancensus R package (von Bergmann et al., 2021). Panel weights were then derived to reflect the weighted cross-sectional distributions, ensuring consistency between the longitudinal subsample and the broader study population. Detailed weighted socio-demographic distributions are presented in the results section.

5. Methods

5.1. Exploratory factor analysis

Exploratory Factor Analysis (EFA) is a statistical technique used to uncover the underlying structure of a set of observed variables by identifying a smaller number of latent constructs, or factors, that account for shared variance (Hair et al., 2014). In this study, we apply EFA to reduce the number of attitudinal and behavioral indicators involved in the analysis while minimizing information loss, thereby providing a more structured input for the subsequent clustering analysis. The variables analyzed include perceptions of the REM, perceptions of gentrification, attitudes toward residential selection, and current transport mode use. Attitudinal questions were asked on a 5-point Likert scale, while mode shares were derived from reported frequency of active travel, driving, and public transit use during the past seven days.

We conducted EFA separately for each survey wave using the *psych* and *factoextra* packages in R, based on Pearson correlation matrices. Factors were extracted using the principal factor solution within EFA, a common approach when the goal is data reduction. The number of retained factors was determined using both the latent root criterion (eigenvalues ≥ 1) and parallel analysis, which has been found to provide more accurate guidance than scree plots alone (Zwick & Velicer, 1986). To improve interpretability and minimize cross-loadings, we applied varimax rotation (Hair et al., 2014). Factor loadings (i.e., the strength and direction of the relationship between each observed variable and its underlying factor) were used to evaluate contributions. Higher loadings indicate stronger associations, and only variables with loadings ≥ 0.5 were retained to ensure meaningful contributions given our sample sizes. Prior to conducting EFA, the factorability of the data was confirmed through standard diagnostics: each variable correlated at $r \geq 0.3$ with at least one other variable, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeded the 0.7 threshold, and Bartlett's test of sphericity was statistically significant, confirming that the correlation matrix was not an identity matrix.

5.2. *Understanding market profiles using weighted k-means clustering*

To identify distinct market profiles, we applied a weighted k-means clustering algorithm to a combination of factor scores and independent variables. K-means is a centroid-based method that partitions observations into clusters by assigning each case to the nearest cluster centroid. Centroids are then updated iteratively to minimize within-cluster variance while maximizing differences between clusters (Hair et al., 2014). This approach has been widely used in transport research and has proven effective for transit market segmentation (Carvalho & El-Geneidy, 2024; Krizek & El-Geneidy, 2007; Van Lierop & El-Geneidy, 2017).

Clustering was conducted separately for the pre-implementation (2022) and post-implementation (2024) samples to capture how market structures evolved following the opening of the REM. For the 2022 segmentation, inputs included factor scores from the exploratory factor analysis along with four independent variables: stated intention to use the REM, transit mode share, frequency of telecommuting, and a low-income indicator (annual household income below CAD $60,000). For the 2024 segmentation, three comparable factor scores remained. Due to a change in survey design, only one gentrification-related item was available, and it was therefore included as a standalone variable. Four independent variables were incorporated: frequency of REM use, transit mode share, telecommuting frequency, and the low-income indicator. All variables were standardized using the *scale* function in R to ensure equal contribution to the clustering process.

The clustering was implemented with the *kcca* function from the *flexclust* package in R, which allows the use of survey weights. As described in the *Data Sources* section, weights were derived through an iterative raking procedure to align the sample with census distributions, ensuring that the resulting clusters are spatially and demographically representative of the study area population. To determine the optimal number of clusters, we tested solutions ranging from three to eight groups, following recommendations in transit segmentation research (Damant-Sirois et al., 2014). Final cluster selection was guided by both statistical diagnostics and substantive criteria. Silhouette analysis was used to assess cluster separation, while transport-specific criteria, such as distinctiveness, relevance to planning, consistency with prior studies, and interpretability, ensured practical and meaningful segmentation (Krizek & El-Geneidy, 2007; Van Lierop & El-Geneidy, 2017). The resulting market profiles form the basis for assessing longitudinal market stability and evaluating how stated intentions align with revealed behavior in subsequent analyses.

Across both survey waves, the weighted clustering consistently yielded a four-cluster solution with comparable attitudinal and behavioral dimensions. While the descriptive labels were updated post-implementation to reflect actual REM use, the underlying market profiles remained stable. Importantly, both segmentation exercises drew on a parallel set of variables ensuring substantive comparability across waves. This parallel structure allows observed transitions to be interpreted as genuine demographic or behavioral changes rather than methodological artifacts.

5.3. *Longitudinal analysis and shifts in the transit market*

To assess how individual travel behavior and cluster membership changed over time at a more disaggregate level, we incorporated a longitudinal component into our methods. By evaluating each individual's trajectory from their pre-REM cluster in 2022 (Wave 3) to their post-REM cluster in 2024 (Wave 5), we could determine the extent to which stated intentions were realized into actual usage or whether preferences shifted in unforeseen ways. The analysis proceeded in three steps.

First, we replicated the factor and cluster analyses on the weighted panel subsample to confirm that the latent attitudinal dimensions and resulting cluster profiles were consistent with those identified in the full cross-sectional samples. Because the validation returned highly similar structures, we retained the clusters derived from the cross-sectional analysis for the panel sample. This ensured that longitudinal transitions could be interpreted within a common market framework. The panel replication served solely as a validation; all longitudinal transitions use the wave-specific cluster labels assigned from the full weighted cross-sectional k-means solutions, not a re-estimation on the panel sample.

Second, we constructed transition flows from respondents' original 2022 cluster assignments to their 2024 counterparts. To align the panel with the population distributions observed in the cross-sectional samples, survey weights were recalibrated using iterative proportional fitting (*anesrake*). The calibrated panel was then used to generate Sankey diagrams that visually illustrate movements between pre-launch intention-based clusters and post-launch behavioral clusters. This procedure allowed us to estimate transitions at the population level rather than reflect only the composition of the panel sample, consequently highlighting both the share of individuals who switched market segments and those who remained stable over time. All transition shares are reported as survey-weighted proportions. To indicate precision, we report 95 % confidence intervals (Wald) from these proportions calculated using the *survey* package reported in the Appendix: Table A. Because some flows are rare and weights reduce the effective sample size, intervals are wider for small counts. Therefore, we focus interpretation in the main text on transitions greater than or equal to 10 %.

Finally, we derived cross-tabulations linking 2022 base clusters and stated intentions to 2024 REM usage frequency, grouped into four categories (once a week or more, weekly or monthly, occasional, and never). Weighted row percentages provide insights into how each cluster–intention group translated into different levels of actual use.

6. Results

6.1. *Structure and stability of market profiles over time*

To assess how attitudinal and behavioral patterns evolved in response to the implementation of the REM, this section presents the factor structures used to segment the market, and the resulting clusters of user profiles identified before and after implementation.

6.1.1. *Exploratory factor analysis*

Tables 1 and 2 present the results of the exploratory factor analyses for the pre- and post-REM samples. In 2022, four factors were identified: perceived benefits of the REM, car-oriented behavior, gentrification concerns, and walkability-oriented behavior. Together, these constructs explained 49.6 % of the total variance. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.77, and Bartlett's Test of

Table 1
Factor loadings for the 2022 sample of survey respondents.

Factor	Variable	Loadings	Cronbach Alpha
Perceived benefits	The REM will be a good thing for the Greater Montréal area.	0.691	0.830
	The REM will be a good thing for my neighborhood.	0.621	
	The REM will be good for Montréal's culture and heritage.	0.709	
	The REM will be good for the environment.	0.706	
	The REM will be good for businesses.	0.799	
Car-oriented behavior	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.	0.624	0.512
	I have regular access to at least one private automobile in my household.	0.683	
	Share of driving in the past seven days (%)	0.757	
Gentrification concerns	I am concerned about whether I will be able to remain in my neighborhood because of rising costs.	0.737	0.697
	I am concerned about whether I will be able to remain in my neighborhood due to rising housing costs with the REM operational.	0.727	
Walkability-oriented behavior	Being near shops and services was an important factor in my decision to move into my current home.	0.639	0.618
	Being near public transportation was an important factor in my decision to move into my current home.	0.590	
	Being near parks and green spaces	0.540	

Variance Explain. (49.6 %); KMO (0.77); Bartlett's Test of Sphericity (χ^2 = 2253.678, d.f. = 78, p-value=0).

Table 2
Factor loadings for the 2024 sample of survey respondents.

Factor	Variable	Loadings	Cronbach Alpha
Perceived benefits	The REM will be a good thing for the Greater Montréal area.	0.791	0.806
	The REM will be good for the environment.	0.764	
	The REM will be good for businesses.	0.720	
Car-oriented behavior	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.	0.688	0.544
	I have regular access to at least one private automobile in my household.	0.704	
	Share of driving in the past seven days (%)	0.659	
Walkability-oriented behavior	Being near shops and services was an important factor in my decision to move into my current home.	0.683	0.672
	Being near public transportation was an important factor in my decision to move into my current home.	0.674	
	Being in a neighborhood where it is a pleasant to walk was an important factor in my decision to move into my current home.	0.565	

Variance Explain. (51.2 %); KMO (0.72); Bartlett's Test of Sphericity (χ^2 = 3881.606, d.f. = 36, p-value=0).

Sphericity confirmed the appropriateness of factor extraction (χ^2 = 2253.678, $p < 0.001$). These dimensions captured both forward-looking attitudes (e.g., pre-launch perceived REM benefits) and mobility-related behavioral patterns, providing a nuanced foundation for market segmentation prior to the system's launch.

In 2024, three comparable factors were extracted: post-launch perceived benefits of the REM, car-oriented behavior, and walkability-oriented behavior. Together, they explained 51.2 % of the variance, with internal consistency levels similar to the pre-launch sample. The sample remained adequate for factor analysis (KMO = 0.72; Bartlett's χ^2 = 3881.606, $p < 0.001$). Due to changes in the survey instrument, only a single gentrification-related item was available, preventing the formation of a latent factor for that dimension. While this limits comparability on that specific construct, the stability of the other factors over time supports the validity of comparing pre- and post-REM conditions.

6.1.2. Weighted k-means clustering: identifying market segments

A cluster solution of four profiles was found to provide the best qualitative description of the market at both points in time (Figs. 3 and 4). Cluster labels were assigned based on the dominant attitudes, behaviors, and socio-demographic traits observed within each group. In the pre-implementation period (2022), the clusters were identified as potential REM adopters, potential REM telecommuters, car-oriented individuals, and low-income individuals. These profiles reflect significant contrasts in attitudinal orientations, socio-economic characteristics, and stated intentions toward the REM (Table 3). Following implementation (2024), a similar segmentation structure emerged. The clusters were characterized as frequent REM riders, telecommuter REM riders, car-oriented individuals, and low-income individuals (Table 4). While the labels were adjusted to reflect actual REM usage patterns, the underlying attitudinal and socio-demographic dimensions remained consistent. The persistence of this four-cluster solution across both survey waves indicates that the fundamental segmentation of the transit market remained stable through the opening of the South Shore branch. No new market segments emerged in the post-implementation period, indicating that the attitudinal and structural composition of the market remained largely intact. Tables 3 and 4 summarize the descriptive statistics for each cluster, including socio-demographic characteristics, travel behavior patterns, REM intentions and usage, and transit-related attitudes.

Pre-REM markets

Potential REM adopter (17 %): This group is characterized by a strong reliance on public transit, with 62 % of trips in the past week made by public transit, compared to only 15 % in the weighted regional average. Their low levels of car use (10 %) and reduced access to private vehicles (52.7 %) further underscore this orientation. Socio-economically, 42.6 % of respondents report annual household incomes of 60,000 CAD or less, a higher share of low-income households than the regional average of 35.9 %. Demographically, the segment is predominantly female (64.6 %) and of working age (95.9 %) with the highest proportion of students among all clusters (38.2 %). Attitudinally, they show strong support for the REM, with 86.4 % believing it would benefit the Greater Montréal. Notably, 84.5 % of respondents in this segment indicated an intention to use the REM prior to its opening, most often citing reduced travel time as a main motivator.

Potential REM telecommuter (36 %): This was the largest group in 2022, likely reflecting pandemic-related shifts toward remote work. Members of this segment telecommute more frequently than the weighted regional average, reporting 2.2 days per week compared to 1.5

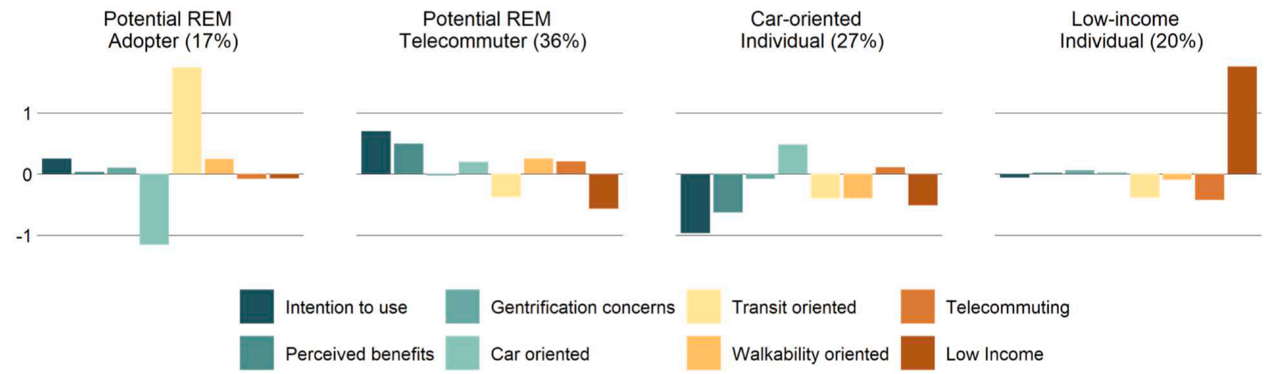

Fig. 3. Identified market profiles pre-REM implementation (2022: $N = 623$).

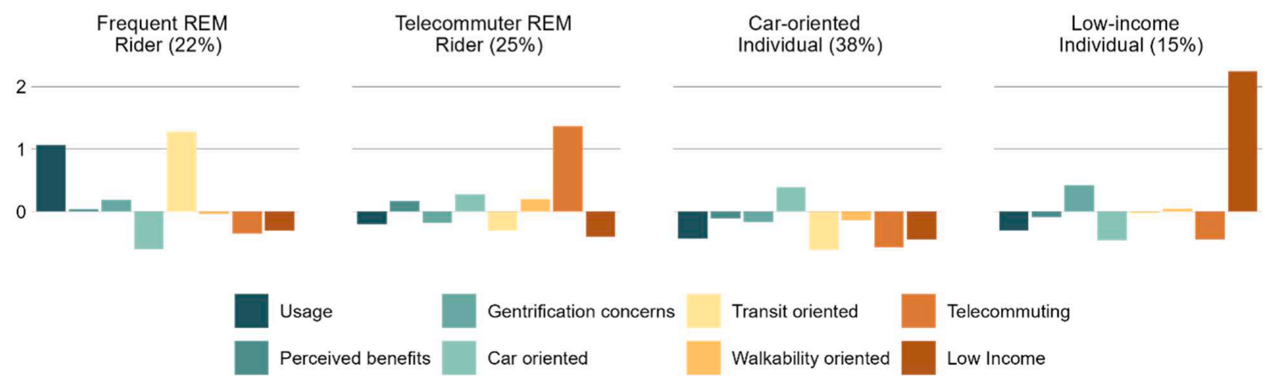

Fig. 4. Identified market profiles post-REM implementation (2024: $N = 1645$).

days. Despite their heavy reliance on private vehicles (i.e., 93.6 % have access to a car, and 72 % of their trips are made by driving), they express strong support for the REM. A large majority (93.3 %) believe the system would be beneficial for the Greater Montréal, and all respondents in this group (100 %) anticipated using the REM once operational often citing reduced travel times as their primary motivation. Demographically, the segment is predominantly of working age (81.2 %) and slightly male-skewed (56.8 %). Although characterized by high car access and use, their stated intention to adopt the REM suggests latent demand that could be fulfilled if the service aligns with their travel needs.

Car-oriented individual (27 %): This was the second largest group, reflecting the suburban and automobile-oriented character of the South Shore. Nearly all respondents in this cluster (97.9 %) report access to a private vehicle, and 86 % of their trips in the past week were made by car, compared to 62 % for the weighted regional average. Transit use is almost negligible, representing only 2 % of trips. Socio-economically, the group is evenly split by gender and is primarily composed of middle- (60k–120k CAD, 53.7 %) and high-income (over 120k CAD, 42.7 %) households. Demographically, middle-aged respondents (36–64 years) are overrepresented (66.1 %) relative to the weighted regional average (52.2 %). On average, members telecommute 1.9 days per week, the second highest among all groups. Attitudinally, they express weaker support for transit: only 71.7 % view the REM positively (compared to 83.7 % overall), and just 35.1 % would recommend Montréal's transit system. Their likelihood of adopting the REM is limited, with only 29.7 % stating they intended to use it once operational. A key reason for this reluctance is geographic: this group lives the farthest from the REM, averaging 11.6 km to the nearest station, with distance frequently being flagged as a barrier to adoption. Overall, this segment represents the least transit-inclined market, highlighting the challenges of attracting car-dependent households to new transit infrastructure.

Low-income individual (20 %): All respondents in this cluster report annual household incomes of 60,000 CAD or less. Travel behavior is primarily car-oriented, with 68 % of trips made by car, though this group also displays a comparatively higher share of active travel (22 %). Car access remains common, with 87.3 % reporting availability of a private vehicle. Demographically, the group has an even gender split and includes a higher proportion of older adults (37.1 %) relative to the regional average (20.3 %). A slightly higher share of respondents report limited mobility (21.8 %) compared to the regional average (16.3 %). Attitudinally, support for the REM is positive, with 81 % believing the system would be good for Montréal. Their intention to use the REM is lower than average, with 59.8 % expressing plans to ride it compared to 70.1 % overall. Among those intending to adopt, shorter travel times and lower costs relative to other modes were the most frequently cited reasons. The combination of low income and greater mobility challenges suggests a group for whom affordability and accessibility are key determinants of adoption.

Post-REM markets

Frequent REM rider (22 %): This group shares many socio-demographic and behavioral characteristics with the pre-launch *potential REM adopters*. They remain strongly transit-oriented, with 62 % of trips made by transit and only 21 % by car, though car access is somewhat higher than in the earlier adopter group (69.8 % versus 52.7 %). Socio-economically, most respondents fall within the middle-income bracket (62 %), while still maintaining a higher proportion of low-income households (20.4 %) relative to other non–low-income clusters. Demographically, the group is predominantly of working age (95.6 %) and slightly more female (55.6 %). Students continue to be over-represented, accounting for 39.8 % of the group. A defining feature of this segment is its high level of REM adoption: 44.1 % report using the system daily and an additional 30.4 % more than once a week, distinguishing this group as the most frequent users of the new infrastructure among the post-launch market profiles.

Telecommuter REM rider (25 %): This group resembles the pre-launch *potential REM telecommuters*, though it now represents a smaller

Table 3
Socio-demographic and behavioral characteristics of the pre-implementation (2022) REM market segments.

Variable	Potential REM Adopter	Potential REM Telecommuter	Car-oriented individual	Low-income Individual	2022 sample
Share	17 %	36 %	27 %	20 %	100 %
Sociodemographic characteristics					
Gender[1]					
Female	64.60 %	43.10 %	50.10 %	51.30 %	51.10 %
Male	35.40 %	56.80 %	49.70 %	48.10 %	48.60 %
Age					
18 to 35	47.90 %	33.90 %	17.90 %	13.90 %	27.50 %
36 to 64	47.60 %	47.30 %	66.10 %	49.00 %	52.20 %
65 and over	4.50 %	18.80 %	16.00 %	37.10 %	20.30 %
Reported disability	13.90 %	14.20 %	15.10 %	21.80 %	16.30 %
Income [in CAD]					
Below 60 k	42.60 %	0.00 %	3.60 %	100.00 %	35.90 %
60 k-120 k	34.20 %	53.50 %	53.70 %	0.00 %	35.50 %
Over 120 k	23.20 %	46.50 %	42.70 %	0.00 %	28.60 %
Employment status					
Worker	69.40 %	71.40 %	77.60 %	33.80 %	62.40 %
Student	38.20 %	6.30 %	3.70 %	9.40 %	12.80 %
Telecommuting frequency [over 7 days][2]	1.01 (1.61)	2.17 (2.38)	1.93 (2.17)	0.63 (1.69)	1.47 (2.12)
Access to at least one private automobile [per household]	52.70 %	93.60 %	97.90 %	87.30 %	84.90 %
Mode Share					
Car share (last 7 days)[2]	10 % (15 %)	72 % (34 %)	86 % (0.23)	68 % (40 %)	62 % (41 %)
Transit share (last 7 days)[2]	62 % (23 %)	4 % (9 %)	2 % (8 %)	4 % (10 %)	15 % (27 %)
Active share (last 7 days)[2]	28 % (26 %)	22 % (31 %)	11 % (21 %)	26 % (37 %)	22 % (31 %)
REM perceptions and intentions					
Intention to use	84.50 %	100.00 %	29.70 %	59.80 %	70.10 %
Distance to the closest REM station [in km][2]	6.43 (7.39)	5.81 (6.02)	11.59 (8.73)	8.26 (7.40)	7.91 (7.67)
Reasons for adoption					
Main reason for use: I will have a shorter travel time	56.90 %	57.10 %	11.50 %	28.70 %	39.00 %
Main reason for use: It will be cheaper than other modes	25.60 %	30.30 %	4.50 %	33.30 %	24.30 %
Main reason to NOT use: It is out of my way or too far to get to	11.70 %	0.00 %	31.80 %	12.90 %	13.00 %
Main reason to NOT use: It won't go where I want to go	3.20 %	0.00 %	24.50 %	15.10 %	10.30 %
Support for the REM being positive for Greater Montreal[3]	86.40 %	93.30 %	71.70 %	81.00 %	83.70 %

[1] Non-binary category was omitted;.
[2] Mean (standard deviation);.
[3] Neutral was considered as no.

share of the market (25 % compared to 38 % before). Members of this cluster continue to telecommute more frequently than any other group, averaging four days per week compared to the weighted regional average of 1.2 days. Despite their strong reliance on private vehicles (i. e., 92.7 % have car access, and 68 % of trips are made by car), REM adoption has taken hold: 26 % use the system more than once a week, and another 24.8 % ride a few times per month. Their main motivation for adoption remains shorter travel times. Transit use overall has increased to 12 %, up from 4 % in the pre-launch period, suggesting that the REM has led to a modest mode shift away from car use. Demographically, the group remains overwhelmingly of working age (97.7 %), but the earlier male skew has disappeared. Overall, this segment demonstrates that the REM has gained traction among telecommuters, though it has not replaced car travel as their primary mode. Instead, adoption appears to be partial, with the REM supplementing rather than displacing their continued reliance on private vehicles.

Car-oriented individual (38 %): This segment expanded considerably following the REM's launch, growing from 27 % to 38 % of the market. As in the pre-implementation period, members remain heavily reliant on private vehicles: cars account for 78 % of their trips, 94.3 % report car access, and transit use is minimal at only 3 %. Compared to the earlier group, this cluster is now slightly male-skewed (53.4 %) rather than evenly split by gender. Socio-economically, middle-income households dominate (56.2 %), with the remainder primarily in higher-income brackets (18 %). Telecommuting has become far less common in this segment, averaging just 0.3 days per week compared to nearly two days pre-REM implementation. Geographically, these respondents still live the farthest from REM stations, with an average distance of 9.3 km. Unsurprisingly, most either do not use the system at all (44.6 %) or ride only occasionally (33.4 %). The most frequently cited reasons for non-adoption are that the REM is too far or does not serve their destinations. Overall, this segment underscores the challenges of attracting car-dependent households located farther from the network, despite incremental improvements in overall system perceptions.

Low-income individual (15 %): This segment continues to be defined by annual household incomes of 60,000 CAD or less. Their travel behavior is still primarily car-oriented, with cars accounting for 52 % of trips, though this is slightly lower than the regional average and the car-oriented cluster. Active travel makes up a comparatively larger share (29 %), while transit use has increased markedly to 17 % from just 4 % pre-REM. Car access is reported by 67.5 % of respondents, a proportion similar to *frequent REM riders* (69.8 %). However, unlike for *frequent REM riders*, lower car access does not translate into frequent REM adoption. Demographically, the cluster is slightly female-skewed (52.8 %) and includes a higher share of older adults (29.6 %). A larger proportion report disabilities or limited mobility (17.3 %), reflecting greater accessibility challenges relative to the regional average. REM adoption is limited: 46.9 % of respondents have never used the system, while 26.2 % report occasional use. Non-adoption is most often attributed to distance from stations or the system not serving their key destinations. Overall, this cluster reflects a population with constrained resources and mobility challenges, where modest gains in transit use since the pre-launch period have not yet translated into widespread REM adoption.

Table 4
Socio-demographic and behavioral characteristics of the post-implementation (2024) REM market segments.

Variable	Frequent REM rider	Telecommuter REM rider	Car-oriented individual	Low-income Individual	2024 sample
Share	22 %	25 %	38 %	15 %	100 %
Sociodemographic characteristics					
Gender[1]					
Female	55.60 %	52.90 %	46.50 %	52.80 %	51.20 %
Male	43.90 %	46.90 %	53.40 %	46.90 %	48.60 %
Age					
18 to 35	46.20 %	33.80 %	21.80 %	29.10 %	29.70 %
36 to 64	49.40 %	63.90 %	56.10 %	41.30 %	52.20 %
65 and over	4.40 %	2.30 %	22.10 %	29.60 %	18.10 %
Reported disability	6.20 %	11.30 %	14.20 %	17.30 %	13.40 %
Income [in CAD]					
Below 60 k	20.40 %	5.60 %	0.00 %	100.00 %	43.90 %
60 k-120 k	66.90 %	73.10 %	82.00 %	0.00 %	45.60 %
Over 120 k	12.70 %	21.30 %	18.00 %	0.00 %	10.50 %
Employment status					
Worker	73.60 %	100.00 %	55.90 %	43.80 %	63.70 %
Student	39.80 %	3.30 %	7.70 %	21.50 %	15.90 %
Telecommuting frequency [over 7 days][2]	0.85 (1.38)	4.05 (1.49)	0.29 (0.65)	0.40 (1.06)	1.18 (1.84)
Access to at least one private automobile [per household]	69.80 %	92.70 %	94.30 %	67.50 %	81.90 %
Mode Share					
Car share (last 7 days)[2]	21 % (23 %)	68 % (33 %)	78 % (32 %)	52 % (43 %)	59 % (40 %)
Transit share (last 7 days)[2]	62 % (27 %)	12 % (16 %)	3 % (11 %)	17 % (28 %)	18 % (28 %)
Active share (last 7 days)2	17 % (22 %)	20 % (29 %)	18 % (29 %)	29 % (34 %)	22 % (30 %)
REM perceptions and usage					
REM usage					
Once a week or more	74.50 %	26.00 %	4.10 %	12.00 %	21.40 %
Weekly or monthly	7.40 %	24.80 %	17.90 %	14.80 %	16.80 %
Occasional	11.00 %	23.90 %	33.40 %	26.20 %	25.90 %
Never	7.10 %	25.20 %	44.60 %	46.90 %	35.80 %
Distance to the closest REM station [in km][2]	5.12 (5.10)	7.65 (7.09)	9.28 (8.47)	7.46 (7.35)	7.78 (7.53)
Reasons for adoption					
Main reason for use: I have a shorter travel time	33.80 %	21.80 %	5.80 %	9.10 %	14.20 %
Main reason for use: It will be cheaper than other modes	20.70 %	11.90 %	4.20 %	4.50 %	8.30 %
Main reason to NOT use: It is out of my way or too far to get to	3.00 %	14.50 %	19.30 %	23.80 %	17.30 %
Main reason to NOT use: It doesn't go where I want to go	5.00 %	12.00 %	23.20 %	17.70 %	16.50 %
Support for the REM being positive for Greater Montreal[3]	84.50 %	83.80 %	79.10 %	81.80 %	81.70 %

[1] Non-binary category was omitted;.
[2] Mean (standard deviation);.
[3] Neutral was considered as no.

Changes in mode share and trip purposes (intended vs. observed)

To further illustrate cluster differences over time, Fig. 5 compares mode shares and primary trip purposes across the identified clusters before and after operation of the REM branch. The results reinforce the descriptive profiles: pre-launch *potential REM adopters* were the most transit-oriented, while *car-oriented individuals* showed a strong reliance on private vehicles. Low-income individuals combined car use with comparatively high levels of active travel. Post-launch, *frequent REM riders* stand out for their heavy reliance on transit, while *telecommuter*

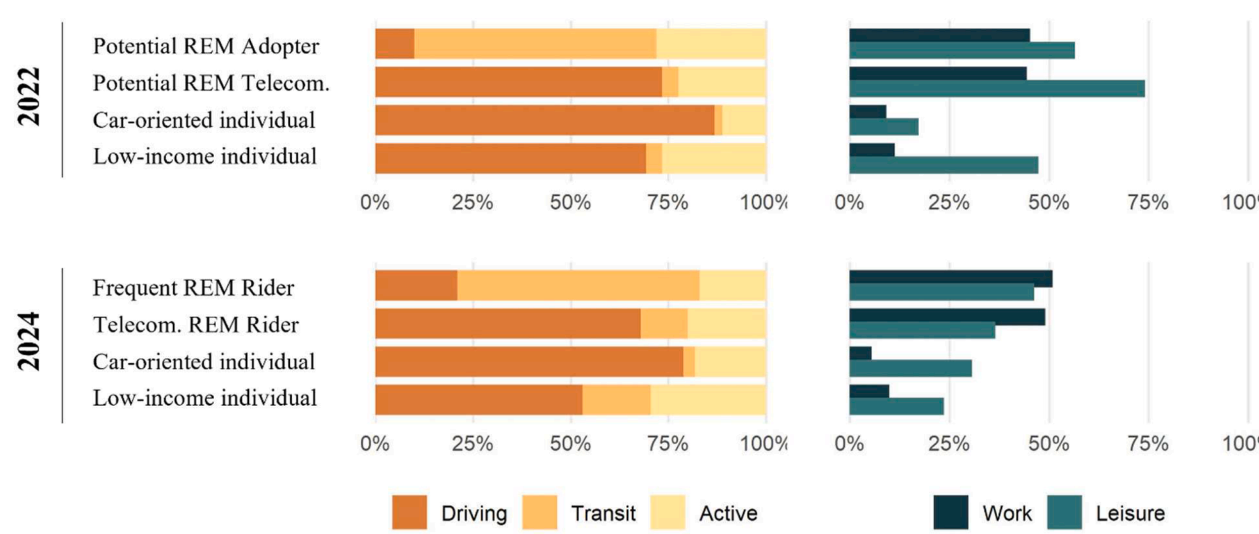

Fig. 5. 2022 and 2024 mode shares and REM trip purposes (2022: $N = 623$; 2024: $N = 1645$).

REM riders, though more car-dependent, showed a slight increase in transit use compared to their pre-launch counterparts.

Across both waves, work and leisure emerge as the dominant trip purposes, but their relative importance differs before and after the REM's launch. In the pre-launch period, intended REM use was often framed around leisure trips. By contrast, in the post-launch period, actual usage shifted more clearly toward work-related travel, especially among *frequent REM riders* and *telecommuter REM riders*. Nonetheless, leisure remains a sizeable share of use in most clusters, suggesting that the REM supports both everyday commuting and discretionary activities.

Taken together, the segmentation results reveal a stable set of market profiles both before and after the REM's implementation. While modal behaviors and demographic compositions shifted slightly within certain groups, the overall structure of the market remained consistent, with no new clusters emerging in the post-launch period. To build on these findings, the following section turns to the longitudinal sample to examine how individual respondents moved within or across these profiles over time. This analysis explores profile stability using a Sankey diagram and cross-tabulations linking 2022 clusters and stated intentions to 2024 REM usage frequency.

6.2. Individual-level market profile transitions over time

The longitudinal sample allows us to examine how individuals shifted across market profiles between the pre-REM period (2022) and the post-REM period (2024). Fig. 6 presents a Sankey diagram that traces these transitions. Using the weighted panel sample, we tracked transitions to assess the degree of consistency in users' attitudinal and behavioral orientations over time, providing insight into the dynamics of modal shift and user adaptation in response to new infrastructure. We focus interpretation on transitions ≥10 % within an origin cluster.

The results reveal both continuity and fluidity across groups. *Potential REM adopters* displayed the highest stability of intention and behavior, with 71.1 % becoming *frequent REM riders* after the system opened. This outcome broadly confirms their high pre-launch intention to adopt the REM (84.5 %) and indicates that many translated intentions into frequent use. Smaller shares transitioned to *telecommuter REM riders* (10.6 %), *car-oriented individuals* (10.4 %), or *low-income individuals* (7.8 %), showing that even among transit-oriented users, some diverged toward alternative mobility patterns.

In contrast, Potential REM telecommuters were far more fluid. Only 38.7 % became *telecommuter REM riders*, typically using the REM a few times a week or month in line with telecommuting patterns. The largest share (46.0 %) shifted to *car-oriented individuals*, reflecting the suburban, automobile-oriented context of the South Shore. Another 13.1 % became *frequent REM riders*, reflecting reduced telecommuting and deeper changes in travel behavior. These patterns suggest that post-pandemic adjustments in work routines translated into sustained telecommuting for some and reversion to car dependence for others.

Car-oriented individuals were overall a stable group. A majority (56.9 %) remained car-oriented, while 28.4 % shifted toward *telecommuter REM riders*, a cluster that still relies heavily on cars despite some REM use. Only a minority (7.9 %) became *frequent REM riders*. Finally, *low-income individuals* also showed stability, with 54.8 % remaining in the same cluster. Others transitioned to *car-oriented individuals* (22.3 %) or, to a lesser extent, to *frequent REM riders* (13.8 %).

Taken together, the findings indicate that the REM's launch reshaped

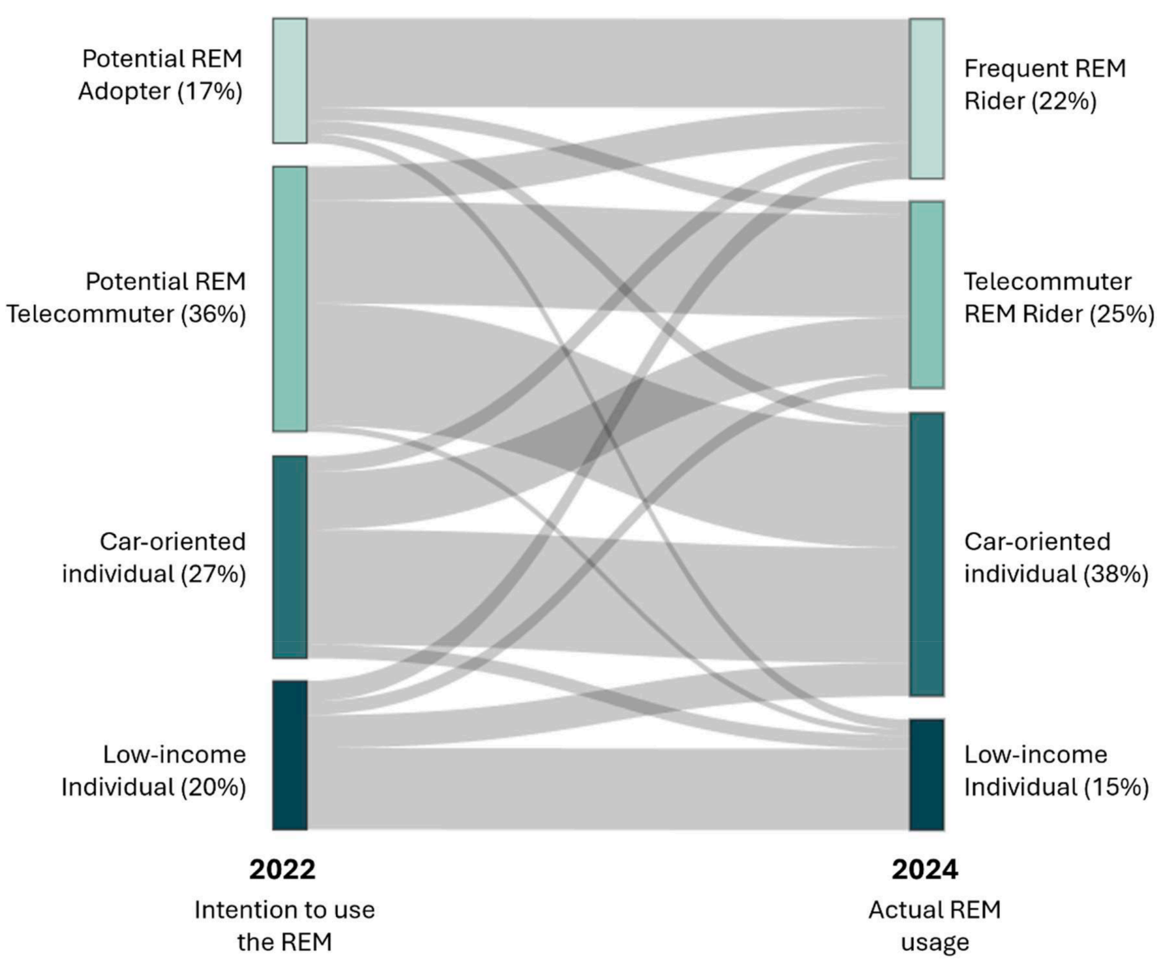

Fig. 6. Longitudinal analysis of the REM market.

the relative size of existing clusters rather than generating entirely new ones. Intention-based groups, such as *potential REM adopters*, largely translated their pre-launch expectations into ridership, while others, particularly *potential REM telecommuters*, were more likely to shift toward car dependence. These transitions reveal both stability and change at the individual level: some respondents remained anchored in long-standing habitual mobility patterns, while others reoriented their behavior with the arrival of the new system. Overall, the longitudinal analysis highlights how the implementation of the REM influenced individual trajectories while leaving the broader market segmentation structure mostly unchanged. This analysis, however, does not fully capture how individuals stated intentions before the REM opening aligned with their actual usage afterward, therefore more detailed analysis is needed to examine intention–behavior alignment more directly. In the next section, we do so by linking pre-launch expectations to post-launch ridership outcomes at the segment level.

6.3. Alignment of intentions to behaviors

Examining how pre-implementation intentions translated into post-implementation behavior reveals both strong alignments and notable mismatches across the market segments (Table 5). Among *potential REM adopters*, the large majority stated they intended to use the system (84.5 %), and this intention largely materialized: almost half (42.5 %) became frequent users and another 43.7 % adopted the system occasionally. Interestingly, even within the minority who initially declared no intention to ride (15.5 %), most ended up doing so, with 81 % using the REM on a weekly basis or more. This intention-behavior divergence underscores the potential for new infrastructure to attract riders even among those initially hesitant, particularly among those already favorable towards the new infrastructure project.

By contrast, *potential REM telecommuters* displayed a more complex pattern. Every respondent in this segment had indicated an intention to use the REM, yet actual behavior was mixed: just over a third (35.1 %) became frequent users, another third (33.0 %) used it weekly or monthly, while a sizeable minority used it occasionally (15.2 %) or not at all (16.8 %). Here, telecommuting routines appear to mediate adoption, producing a wide spread of outcomes despite unanimous early enthusiasm.

For *car-oriented individuals*, the results reflected much closer alignment between intentions and behavior. The majority of this group had declared no intention of using the REM (70.3 %), and indeed, most did not adopt the system: 57.2 % never used it, while 37.5 % did so only occasionally. Even among the minority who had expressed an intention to ride (29.7 %), actual usage was limited, with no respondents becoming frequent users and nearly half (45.4 %) never boarding the system at all. A somewhat similar story is seen among *low-income individuals*. While a majority had expressed an intention to use the REM (59.8 %), usage was limited, with just 10.0 % becoming frequent users and nearly half (44.8 %) never adopting the system. Among those who initially expressed no intention to ride (40.2 %), most did not use the REM (79.8 %).

Overall, these findings illustrate that while pre-implementation intentions provide useful signals of likely market adoption, actual behavior often diverges in meaningful ways once new infrastructure becomes available. Segments predisposed to the REM, such as *potential REM adopters*, not only fulfilled their stated intentions but also generated unexpected adoption among initially reluctant individuals. Conversely, groups with structural or attitudinal barriers, such as *car-oriented* or *low-income individuals*, remained largely resistant, despite some expressed willingness to adopt the service. *Potential REM telecommuters*, meanwhile, highlight how lifestyle factors (e.g., telecommuting) complicate the translation of intention into behavior. Together, these patterns underscore the importance of viewing stated intentions as indicative but not deterministic.

7. Discussions

This study contributes to the literature on light rail ridership and market segmentation by providing one of the first longitudinal analyses of how user profiles evolve before and after the introduction of a new LRT system. While most segmentation studies have relied on cross-sectional snapshots, our findings add evidence of how market structures and individual behaviors adjust once a new line is in operation. By combining cross-sectional and longitudinal data from Montréal's REM, the analysis demonstrates both the persistence of broad market profiles and the fluidity of individual-level transitions.

A key finding is the persistence of four market clusters across both survey waves. Despite some shifts in their demographic and behavioral composition, the same set of clusters emerged in 2022 and 2024, and no new groups appeared after the system opened. This suggests that the South Shore branch market remained stable through the REM's introduction. These results extend Dent et al. (2021), who identified intention-based profiles prior to the REM's launch but could not observe their persistence. It is important to highlight that Dent et al. (2021) evaluates the markets around all REM stations while we narrow the focus to currently operational ones, which is a factor explaining the absence of markets, such as *leisure and airport users* in our segmentation. The stability of the segmentation structure reinforces the value of pre-launch segmentation as a planning tool, given that early profiles appear to remain meaningful even once behavior unfolds in practice.

At the same time, the longitudinal analysis reveals more fluidity at the individual level than aggregate stability would suggest. *Potential REM adopters* displayed the strongest alignment between intention and behavior, with over 70 % transitioning into *frequent REM riders* after launch. In contrast, *potential REM telecommuters* were far more fluid, with fewer than 40 % becoming *telecommuter REM riders*, while nearly half reverted toward car-oriented profiles. This pattern highlights how post-pandemic adjustments in work routines translated into divergent travel outcomes, sustaining telecommuting for some while reinforcing auto reliance for others. *Car-oriented individuals* remained the most resistant to change, with a majority staying in the same cluster and a minority consistently adopting the REM, reflecting the difficulty of shifting entrenched driving habits. *Low-income individuals* also showed stability, with small increases in transit use but continued barriers to REM adoption. Overall, these transitions illustrate a duality of stable

Table 5
Intention-behavior alignment holding pre-implementation clusters constant.

Cluster (Before)	Intention	Share	REM use (After)			
			Once a week or more	Weekly or monthly	Occasional	Never
Potential REM Adopter	Yes	84.5 %	42.5 %	1.3 %	43.7 %	12.5 %
	No	15.5 %	81.0 %	0.0 %	18.3 %	0.7 %
Potential REM Telecommuter	Yes	100.0 %	35.1 %	33.0 %	15.2 %	16.8 %
	No	0.0 %	-	-	-	-
Car-oriented individual	Yes	29.7 %	0.0 %	9.2 %	45.3 %	45.4 %
	No	70.3 %	0.0 %	5.3 %	37.5 %	57.2 %
Low-income Individual	Yes	59.8 %	10.0 %	18.8 %	26.4 %	44.8 %
	No	40.2 %	0.0 %	10.2 %	10.1 %	79.8 %

markets but shifting individuals: market profiles persist as meaningful categories, yet individuals within them adjust in response to new opportunities and constraints.

An important barrier shaping REM adoption is telecommuting. Many *potential REM telecommuters* adopted car-oriented profiles after launch, despite initially expressing unanimous intentions to ride the new infrastructure. While some continue to telecommute several days per week and use the REM occasionally, others likely transitioned back to full-time on-site jobs in locations not well served by the system. This is consistent with the very low telecommuting rates observed among post-implementation *car-oriented individuals*. In both cases, evolving work arrangements limit the potential for daily commuting trips to be captured by the REM, even among individuals predisposed to support or adopt the system.

These labor market dynamics intersect with a second, structural barrier: the spatial dimension of the REM within the South Shore. The South Shore branch primarily serves trips destined for downtown Montreal, offering less value to individuals whose jobs, schools, or daily activities are oriented elsewhere in the region. For many suburban residents, the line may not align with their everyday mobility needs, leading to low adoption despite favorable attitudes. The stability of the car-oriented cluster, combined with evidence that distance and limited geographic coverage are key reasons for non-use, underscores this misalignment. These findings suggest that barriers to REM adoption cannot be explained by attitudes alone. Instead, the combination of post-pandemic work practices and the geographic orientation of the network likely influence who benefits from the system. While the REM has successfully converted some intention-based adopters into frequent users, broader shifts in work routines and the suburban structure of the South Shore likely continue to anchor many residents in car-dependent patterns.

Another important finding is that adoption does not always translate into a full modal shift. *Telecommuter REM riders*, for instance, often use the system occasionally while continuing to rely primarily on cars for most trips. This partial adoption expands the REM's reach but limits its immediate capacity to substantially reduce regional car dependence, showing that new infrastructure may only modestly increase transit mode share in the short term without fundamentally altering entrenched habits. However, in the medium to long term, if the REM proves reliable, convenient, and better aligned with residents' needs, adoption levels may grow, and more sustained modal shifts could emerge.

In addition to these behavioral dynamics, the South Shore case highlights how system-level and spatial factors condition adoption. Prior research has shown that ridership is strongest where built environment characteristics and multimodal integration align, including strong bus connectivity, park-and-ride provision, and safe pedestrian access (Currie & Delbosc, 2013; Kim et al., 2007; Kuby et al., 2004). By contrast, the South Shore branch was primarily designed as a downtown connector, limiting its relevance for residents whose work or daily activities are oriented elsewhere in the region. This structural misalignment helps explain why the *car-oriented cluster* not only persisted but expanded after implementation, becoming the largest segment of the post-REM market. Consistent with this outcome, ridership has fallen short of early projections: while 30,000 daily passengers were anticipated, actual counts have averaged closer to 24,000 (CBC News, 2024; CDPQ Infra, 2017; Wanek-Libman, 2023). Respondents frequently cited distance and limited geographic coverage as reasons for non-use, suggesting that supportive attitudes alone are insufficient to generate modal shift in auto-oriented contexts.

Finally, operational performance may be relevant. Since opening, the REM has faced recurring disruptions, both technical and weather-related, that have attracted significant media attention. While our survey does not directly measure perceptions of reliability, it is plausible that service disruptions have tempered adoption, particularly among car-oriented households with viable alternatives. This provides additional context for understanding why actual ridership has lagged behind early projections, alongside the structural barriers discussed above.

7.1. Policy implications

The results of this study offer insights for planners and policymakers aiming to enhance the effectiveness of new transit infrastructure investments. By examining market evolution and gaps in intention and behavior, the analysis reveals not only the stability of market profiles but also the varied behavioral responses among user groups. These findings reinforce the need for differentiated policy strategies tailored to the characteristics and barriers facing each segment.

Potential REM Adopters → Frequent REM Riders: Before implementation, adopters expressed strong intentions to use the REM, and most successfully transitioned into frequent riders. This confirms the system's ability to meet the expectations of its most transit-/REM-oriented supporters. Policy focus now should shift from conversion to retention. Ensuring reliability, minimizing disruptions, and maintaining affordability are critical to sustain this core ridership base, especially since the group includes many students and lower-income households. Protecting their loyalty will secure a foundation of regular riders and help normalize REM use as part of everyday mobility as long as service quality keeps pace with user expectations (Carvalho et al., 2022).

Potential REM Telecommuters → Telecommuter REM Riders: Before launch, nearly all members of this group expressed an intention to use the REM. After implementation, however, many became only occasional users, typically riding a few times per week or month in line with hybrid work patterns. Their continued reliance on cars reflects both flexible work arrangements and the suburban orientation of their daily activities. This outcome is consistent with pandemic-era research showing that telecommuting has reshaped travel routines in ways that persist for some, particularly higher-income individuals, but diminish for others (Brough et al., 2021; Palm et al., 2022). For policymakers, this group represents partial adoption rather than full modal shift. Strategies to increase their ridership should focus on making the REM more attractive for irregular users, such as through flexible fare structures tailored to telecommuters, expanded park-and-ride capacity, and improved last-mile connectivity. Because this segment already engages with the system, even incremental increases in their use could yield significant gains in overall ridership.

Car-Oriented Individuals → Car-Oriented Individuals: This segment was reluctant before launch and became the largest post-launch group (38 %), reflecting both structural barriers and the suburban orientation of the South Shore. Many live farther from REM stations (~9.3 km on average) or have daily activities not oriented toward downtown. Policy interventions should prioritize frequent, reliable feeder bus integration and long-term land use and transport coordinated change going beyond awareness and attitudinal shift campaigns to reduce car dependence (Currie & Delbosc, 2011). However, expectations for major modal shift must remain realistic: strategies may need to focus on specific trip purposes (e.g., downtown commutes, downtown leisure trips) rather than full adoption.

Low-Income Individuals → Low-Income Individuals: Despite limited financial resources, this group remains predominantly car-reliant, with transit continuing to account for the smallest share of their trips. Their limited adoption of the REM is explained not simply by affordability but by structural constraints: many respondents report living too far from stations or that the system does not serve their desired destinations. These barriers are compounded by the group's demographic profile, which includes a higher share of older adults and respondents with disabilities, who may face additional accessibility challenges. For policymakers, this underscores that fare reductions or affordability measures alone will not be sufficient. Improving feeder bus coverage and ensuring universally accessible bus stops and station design are critical to making the REM viable for this market. Without targeted interventions, this group risks being excluded from the benefits of major transit investments, reinforcing existing mobility inequities.

Taken together, the segmentation results highlight that maximizing the benefits of the REM requires a combination of targeted and overlapping policy strategies. Some interventions, such as strengthening feeder bus networks, improving last-mile access, and ensuring reliable operations, would benefit multiple groups simultaneously, from frequent riders who need dependable service to low-income and car-oriented residents who face distance barriers. At the same time, other strategies must be tailored to specific market segments, such as flexible fare options for telecommuters. By grounding policy responses in the distinct needs and barriers of each group, while recognizing the overlaps across them, planners can move beyond one-size-fits-all approaches.

8. Conclusion

This study combined cross-sectional and longitudinal survey data to examine how transit market profiles evolved before and after the opening of Montréal's REM South Shore branch. The analysis revealed both stability in the overall segmentation structure and fluidity in individual trajectories, highlighting that while pre-launch profiles provide useful planning insights, actual adoption is shaped by structural constraints and evolving work practices (e.g., telecommuting patterns). By directly comparing pre-launch intentions with post-launch behaviors, the study also underscores that stated preferences are informative but not deterministic. For policymakers, these findings emphasize that new infrastructure alone cannot ensure modal shift without complementary measures that address geographic coverage, accessibility, and reliability. Limitations include reliance on self-reported ridership rather than observed counts and the short-term frame of study covering only the system's first year of operation. Future research should assess whether similar patterns hold as additional branches open and the network expands.

CRediT authorship contribution statement

Sarah Balaghi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Thiago Carvalho:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Rodrigo Victoriano-Habit:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, 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 have no conflicts of interest to declare that are relevant to the content of this article.

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APPENDIX

Table A

Table A
Confidence intervals of market transitions.

Clusters: Pre-REM	Clusters: Post-REM	Share	95 % CI
Potential REM adopter	Frequent REM rider	71.10 %	[55.8 %, 86.5 %]
Potential REM adopter	Telecommuter REM rider	10.60 %	[1.1 %, 20.2 %]
Potential REM adopter	Car-oriented Individual	10.40 %	[2.5 %, 18.3 %]
Potential REM adopter	Low-income Individual	7.80 %	[1.5 %, 14.1 %]
Potential REM telecommuter	Frequent REM rider	13.10 %	[0.0 %, 29.1 %]
Potential REM telecommuter	Telecommuter REM rider	38.70 %	[24.3 %, 53.1 %]
Potential REM telecommuter	Car-oriented Individual	46.00 %	[31.6 %, 60.4 %]
Potential REM telecommuter	Low-income Individual	2.20 %	[0.0 %, 5.4 %]
Car-oriented Individual	Frequent REM rider	7.90 %	[0.0 %, 22.2 %]
Car-oriented Individual	Telecommuter REM rider	28.40 %	[14.4 %, 42.4 %]
Car-oriented Individual	Car-oriented Individual	56.90 %	[41.3 %, 72.6 %]
Car-oriented Individual	Low-income Individual	6.80 %	[0.9 %, 12.7 %]
Low-income Individual	Frequent REM rider	13.80 %	[0.0 %, 37.6 %]
Low-income Individual	Telecommuter REM rider	9.10 %	[0.0 %, 21.1 %]
Low-income Individual	Car-oriented Individual	22.30 %	[7.6 %, 36.9 %]
Low-income Individual	Low-income Individual	54.80 %	[33.7 %, 75.9 %]

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