Changes in the Public Transit Market for a New Light Rail System: A Before-and-After Study in Montréal, Canada

Sarah Balaghi

May 2025

Supervised by Prof. Ahmed El-Geneidy

Supervised Research Project submitted in partial fulfillment of the requirements of the degree in Urban Planning

McGill

Research Acknowledgment

First and foremost, I would like to thank my supervisor, Professor Ahmed El-Geneidy, for his guidance, support, and trust throughout my degree. His expertise and mentorship have been instrumental in the development of this research and in shaping my growth as a transportation planner.

I would also like to thank the members of the Transportation Research at McGill (TRAM) lab for their continuous encouragement, valuable feedback, and above all, their friendship throughout this journey.

A heartfelt thank you to my friends and family for their patience and unwavering support throughout this process. And a special thank you to my husband for his constant encouragement, reassurance, and for always believing in me every step of the way.

Finally, I would like to thank the School of Urban Planning at McGill University for its academic support and the learning environment that made this work possible.

All photos used in this project have been sourced from the Transportation Research at McGill (TRAM) lab.

Table of Contents

Summary

The Réseau express métropolitain (REM), Montréal's new 67-kilometre automated light rail network, opened its first branch between downtown and the South Shore in August 2023. As one of the largest public transit investments in Canadian history, the REM is expected to have a significant impact on mobility patterns across the metropolitan region. This research contributes to assessing the effects of this new infrastructure on public transit behavior, using a market segmentation approach. Drawing on data from the Montréal Mobility Survey collected in 2022, prior to the REM's opening, and again in 2024 after its launch, the study applies exploratory factor analysis and k-means clustering to identify distinct user segments and track their evolution over time. While user profiles remained generally stable, new segments emerged and changes were observed in travel behavior. The results show that the REM's initial phase of operation introduced new patterns of use and revealed a notable gap between intended and actual usage. Continued monitoring is essential to adapt transit services and better respond to the changing needs of diverse user groups.

Key findings

- A notable share of car-oriented respondents in 2022 transitioned to occasional or frequent REM use by 2024.
- New user segments emerged following the REM's launch, including one characterized by concerns about affordability and neighborhood change.
- Positive attitudes toward the REM did not consistently translate into regular use, highlighting the role of structural barriers such as limited connectivity and service coverage.
- Across all segments, the REM was frequently used for leisure and off-peak travel, suggesting demand beyond traditional commuting patterns.
- While the overall segmentation structure remained stable, several respondents shifted between segments from 2022 to 2024, reflecting changes in their travel habits.
- The longitudinal design revealed a clear discrepancy between intended and actual REM usage, underscoring the value of continued monitoring.

Sommaire

Le Réseau express métropolitain (REM), le nouveau réseau de train léger automatisé de 67 kilomètres à Montréal, a inauguré sa première branche entre le centre-ville et la Rive-Sud en août 2023. En tant que l'un des plus importants investissements en transport collectif de l'histoire canadienne, le REM devrait avoir un impact significatif sur les habitudes de déplacement à l'échelle de la région métropolitaine. Cette recherche contribue à évaluer les effets de cette nouvelle infrastructure sur les comportements en matière de transport en commun, en s'appuyant sur une approche de segmentation du marché. À l'aide des données recueillies dans le cadre du Montréal Mobility Survey en 2022, avant l'ouverture du REM, puis en 2024, après sa mise en service, l'étude utilise une analyse factorielle exploratoire et le k-means pour identifier différents segments d'usagers et suivre leur évolution à travers le temps. Bien que les profils d'usagers soient restés globalement stables, de nouveaux segments ont émergé et des changements ont été observés dans les habitudes de déplacement. Les résultats montrent que la mise en service initiale du REM a entraîné de nouvelles dynamiques d'utilisation et révélé un écart important entre l'usage prévu et l'usage réel. Un suivi continu s'avère essentiel pour adapter l'offre de transport et mieux répondre aux besoins changeants des différents groupes d'usagers.

Principaux résultats

- Une part importante des répondants orientés vers la voiture en 2022 sont devenus des usagers occasionnels ou fréquents du REM en 2024.

- De nouveaux segments d'usagers ont émergé après la mise en service du REM, notamment un groupe préoccupé par les effets de gentrification et l'abordbilité des quartiers.

- Les attitudes positives envers le REM ne se sont pas systématiquement traduites par une utilisation régulière, en raison de barrières structurelles comme la connectivité limitée et la couverture du service.

- Le REM a été largement utilisé pour des déplacements de loisirs et hors pointe, ce qui suggère une demande au-delà des heures de pointe.

- Bien que la structure générale des segments soit demeurée stable, plusieurs répondants ont changé de segment entre 2022 et 2024, ce qui reflète des évolutions dans leurs habitudes de déplacement.

- L'approche longitudinale a mis en évidence un écart entre l'usage prévu et l'usage réel du REM, soulignant l'importance d'un suivi continu.

1 Introduction

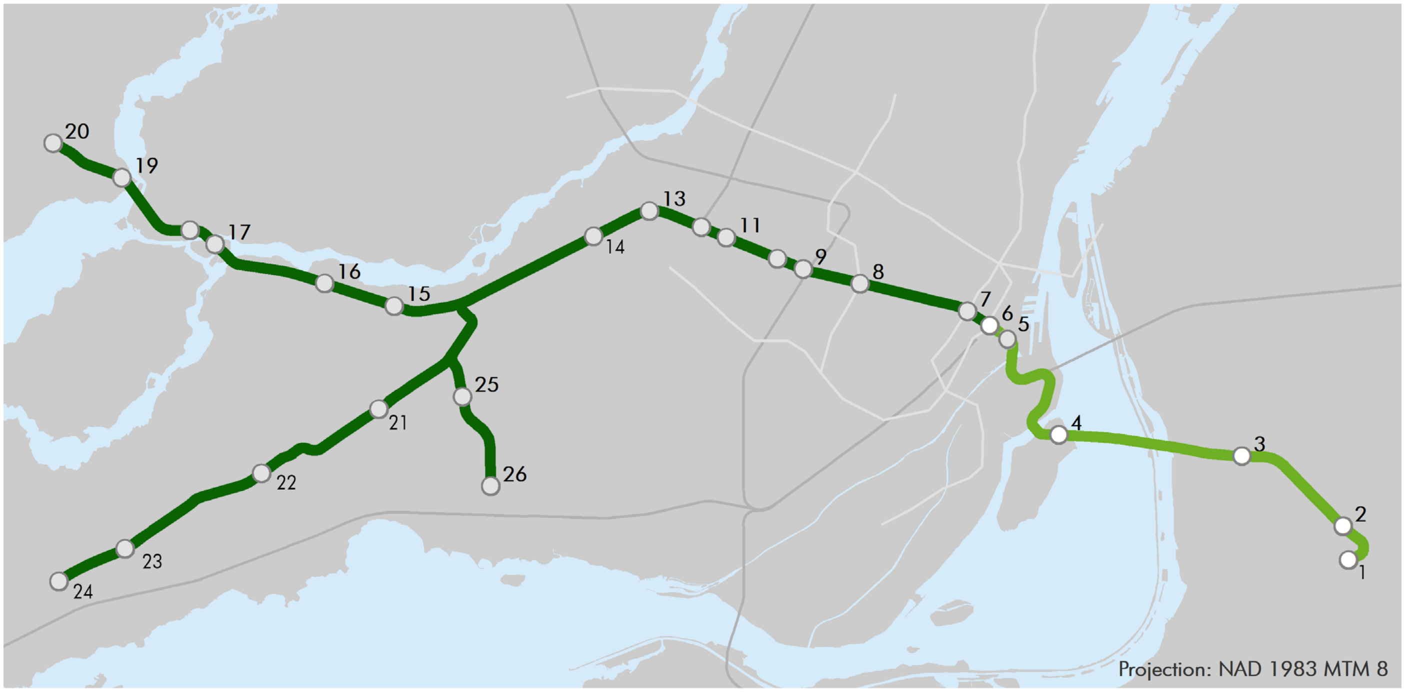
The introduction of large-scale public transit infrastructure often carries the promise of improving regional mobility, reducing car dependency, and fostering sustainable urban development. However, the success of such investments depends not only on the quality of service delivered but also on how different segments of the population respond to the new mobility option (Casello et al., 2015). Because of this, understanding public transit markets through user segmentation has become a central focus in transport research and planning, offering insight into how people's attitudes, behaviors, and personal circumstances shape their engagement with the public transit system (Krizek & El-Geneidy, 2007; Van Lierop & El-Geneidy, 2017). Segmentation approaches are increasingly used to reveal patterns that would otherwise be obscured in aggregate analyses, enabling planners to tailor strategies to different user needs and expectations. They also help identify underserved or vulnerable groups, guiding more equitable investments in service delivery and accessibility.

In August 2023, the Réseau express métropolitain's (REM) first operational segment was launched, connecting the South Shore of Montréal to the downtown core through a new Light Rail Transit system (LRT). The REM, one of the most ambitious transit projects in Canadian history, is a fully electric and automated system and will span 67 kilometers once fully completed. This new system has the potential to significantly reshape travel behavior across the region. Despite strong anticipation surrounding the project, there is limited empirical research on how the public's initial intentions toward the REM have translated into actual usage patterns following the opening of its first branch. Although segmentation frameworks have been applied to understand the potential market before the system's launch (Dent et al., 2021), few studies have tracked the same individuals over time to evaluate how expectations align with real-world behavior. Understanding the difference between intention and action is critical, especially when planners rely on stated-preference data to forecast ridership or justify future transit investment.

This paper addresses that gap by examining shifts in the segments of the public transit market before and after the REM began operations, using data from the Montréal Mobility Survey (MMS). Drawing on both cross-sectional and longitudinal samples from 2022 (pre-REM) and 2024 (post-REM), the study applies exploratory factor analysis and k-means clustering to segment the market based on attitudinal, behavioral, and socio-demographic variables. In addition to identifying market segments at two different points in time, the longitudinal sample allows us to analyze how individuals transition between market segments, offering a novel view of behavioral changes in response to new infrastructure.

The REM presents a rare opportunity to study a large-scale shift in mobility habits in real time, especially in a North American context where car dominance is still prevalent. Insights from this work contribute to broader efforts in demand forecasting, behavior change modeling, and equitable transit planning in rapidly evolving urban regions.

By comparing intended REM usage with observed behavior after the system's launch, this study provides insights for transit planning and policymaking working towards maximizing the benefits of new public transit infrastructure projects, improving service design, and promoting long-term mode shift among diverse user groups.



REM stations

1 - Brossard	10 - Ville de Mont-Royal	19 - Grand-Moulin
2 - Du Quartier	11 - Côte-de-Liese	20 - Deux-Montagnes
3 - Panama	12 - Montpellier	21 - Des Sources
4 - Île-des-Soeurs	13 - Du Ruisseau	22 - Fairview-Pointe-Claire
5 - Griffintown-Bernard-Landry	14 - Bois-Franc	23 - Kirkland
6 - Central Station	15 - Sunnybrooke	24 - L'Anse-à-l'Orme
7 - McGill	16 - Pierrefonds-Roxboro	25 - Marie-Curie
8 - Édouard-Montpetit	17 - Île-Bigras	26 - YUL-Aéroport-Montréal-Trudeau
9 - Canora	18 - Sainte-Dorothée	

REM - operating
REM - under construction
Metro
Commuter train
Data Sources: CDPQ Infra, STM
0 2.5 5 10 Km
N

Figure 1.1 Réseau express métropolitain (REM) line and stations (TRAM, 2023)

2 Literature Review

Research on public transit has extensively examined the factors shaping ridership, from the role of fare structures and quality of service (Currie & Wallis, 2008; Legrain et al., 2019) to built-environment characteristics (Moniruzzaman & Páez, 2012; Owen & Levinson, 2015). This literature has been key in identifying socio-economic, spatial, and psychological factors influencing transit use. However, fully understanding the dynamics of transit usage requires more than independently analyzing ridership levels, attitudes and behavioral tendencies (Anable, 2005; Grise & El-Geneidy, 2018). A framework that has increasingly proven useful for scholars and stakeholders has been market segmentation, helping in unraveling the diversity of the transit market, and the way needs, preferences, habits, and constraints shape travel behavior. 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).

2.2 Market Segmentation in Public

Market segmentation is a widely used framework in public transport planning. One of the earliest distinctions was identified between captive riders and choice riders (E. Beimborn et al., 2003). Captive riders rely on public transit due to economic or physical constraints, while choice riders opt for transit despite having access to alternative modes, often based on convenience or values (Zhao et al., 2014). While this binary framework has been foundational, it has been increasingly critiqued as overly simplistic (E. A. Beimborn et al., 2003; Van Lierop & El-Geneidy, 2017). More recently, Van Lierop and El-Geneidy (2017) proposed a third category, referred to as captive-by-choice riders, who possess the means to choose other modes but prefer transit for experiential or practical reasons.

To address the limitations of binary classification, scholars have adopted more nuanced, data-driven segmentation 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). These methods typically involve techniques like factor analysis and k-means clustering to group transit users by 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) applied clustering to Montréal transit users based on cost and time sensitivity, while Grise and El-Geneidy (2018) focused on user satisfaction attributes such as safety and reliability. These user profiles inform strategies that address both current service quality and future improvements. Geographic segmentation also plays a role in understanding rider experiences, particularly in identifying disparities in access and service perceptions (Chen, 2015; Grise & El-Geneidy, 2018).

Segmentation frameworks have been particularly useful in transit planning for identifying not only current rider characteristics but also potential or latent markets. In Montréal, Van Lierop and El-Geneidy (2017) linked user profiles with neighborhood characteristics, revealing how land use and accessibility shape demand. Jacques et al. (2013) assessed how preferences for cost and service quality vary across groups, offering insights for service adjustments. Dent et al. (2021) contributed to this field by anticipating the REM user market prior to launch, identifying distinct profiles of potential riders based on socio-economic and attitudinal indicators. This work builds on previous studies that looked at users and non-users as part of the public transit market (Krizek & El-Geneidy, 2007) to help in attracting new riders and keeping existing ones.

The COVID-19 pandemic has further transformed transit behavior. Studies have acknowledged the sharp shifts in ridership patterns, increased telecommuting, and changing travel purposes (Carvalho & El-Geneidy, 2024; Palm et al., 2022). These shifts are particularly relevant when interpreting current rider segments, as habits and needs have evolved. Disadvantaged users remained more reliant on transit, while choice riders adapted to remote work and other modes (Brough et al., 2021; Haider & Anwar, 2022). Although trends continue to shift, this behavioral disruption opens opportunities for long-term change, highlighting the value of monitoring user and non-user groups of public transit over time.

Although recent literature continues to evolve, many post-COVID studies still rely on data collected before the pandemic (Guerra, 2022; Jamal et al., 2023; Mesbah et al., 2022; Wang et al., 2022). As a result, segmentation findings may not fully capture the behavioral shifts prompted by the COVID-19 pandemic (Victoriano-Habit & El-Geneidy, 2024). For example, the pandemic altered travel behavior through increased telecommuting, heightened safety concerns, and changes in trip purposes (Carvalho & El-Geneidy, 2024; Palm et al., 2022). Disadvantaged populations remained dependent on public transit while more affluent users adapted to remote work and alternative modes (Brough et al., 2021; Haider & Anwar, 2022). This study responds to this gap by comparing user and non-user profiles before and after the REM's implementation, highlighting how market segments evolved over time in light of broader behavioral and contextual changes.

2.3 Segmentation before and after the emergence of a new transit system

While market segmentation has been widely used to understand transit rider behavior, fewer studies have explored how these segments evolve following the introduction of new transit infrastructure. Most existing research tends to assess either pre-launch expectations (Dent et al., 2021) or post-launch behavior in isolation, using cross-sectional data (Cao & Schoner, 2014; Kim & Ulfarsson, 2012). As a result, limited attention has been paid to how individuals' intended use of a new system aligns with their actual behavior after it opens. Some studies, such as Dent et al. (2021), have offered intention-based segmentation before system launch. However, they do not typically follow up to observe whether anticipated behavior materializes in the long term. This gap in the literature is particularly relevant for projects like Montréal's REM, where public support and usage expectations played a central role in justifying the large investment.

This study addresses this gap by using repeated cross sectional and longitudinal data from the MMS to track individuals before and after the opening of the REM. This approach enables a novel comparison between stated and revealed behavior, offering insight into how rider profiles evolve and how different

3 Data

This study draws on data from the MMS, a multi-wave survey conducted by the Transportation Research at McGill (TRAM) group (Victoriano-Habit et al., 2024). Up to date, five waves have been collected: in the years 2019, 2021, 2022, 2023, and 2024. The MMS collects detailed information on respondents' travel behavior, socio-demographic characteristics, and attitudes toward mobility, making it well-suited to analyze changes in public transit markets over time.

To ensure a large and diverse sample in all waves, the research team applied multiple recruitment strategies. Following the approach proposed by Dillman et al. (2014), participants were recruited through social media advertisements, flyer distribution and personalized email invitations. At each wave, this mobility survey has collected responses from new participants, as well as repeating participants from previous waves. Through this recruitment strategy, the sample comprises both cross-sectional (one-time) observations, as well as panel (repeated) observations. The same data-cleaning protocols were applied across all waves to ensure consistency. These included the exclusion of responses based on short completion time (fastest 5%), duplicate entries from the same email address or IP address, invalid age or height differences between the waves, incomplete answers, and geolocation outside the Montréal metropolitan area.

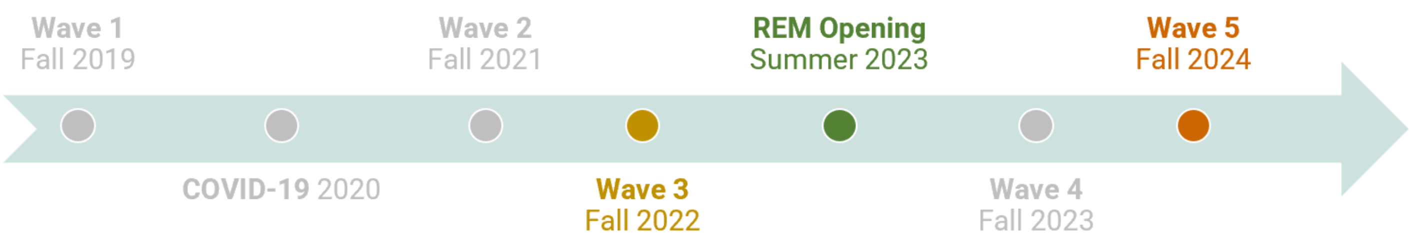


Figure 3.1 Montréal Mobility Survey (MMS) waves

This study focuses on respondents residing within specific spatial boundaries, as illustrated in Figure 1. These boundaries were carefully delineated to capture a sample with realistic access to the new REM infrastructure and a plausible likelihood of incorporating it into their travel routines. The analyzed sample includes the entire South Shore of Montréal, where the REM's first operational segment is currently in service. It also encompasses individuals located within a 2 km buffer around Gare Centrale station on the island of Montréal—an area considered a reasonable catchment for REM access. Additionally, all residents of Nun's Island were included, given the island's small geographic size and its proximity to a REM station, which suggests a strong potential for access to its REM station.

This work relies on both cross-sectional and longitudinal responses from two waves of the MMS. To identify shifts in user profiles and market segmentation before and after the opening of the REM, we utilize data from Wave 3 (2022) and Wave 5 (2024) of the MMS. Wave 3 was selected as it represents the most recent data collected prior to the REM's first segment opening, capturing respondents' baseline travel behavior, intended use of the REM and expectations. Wave 5 is the most recent wave available post-opening, allowing to assess actual usage and travel behavior after the system's first segment became operational. In 2022, 656 cross-sectional valid responses were retained within the study area, and 1,889 in 2024. The longitudinal subsample includes 181 respondents who completed both Wave 3 and Wave 5 of the survey and reside within the defined study area. This panel subsample enables a direct comparison between stated intentions and revealed behavior, offering deeper insights into how travel patterns evolved in response to the opening of the new transit infrastructure.

The MMS collects a wide range of variables related to personal characteristics, travel behaviour, trip satisfaction and travel preferences. The MMS includes more than 300 questions, participants receive a subsample of these questions depending on their knowledge of the REM and other projects in the region, employment status, and the state of the REM construction near their work or home. Detailed information about the MMS can be found in Victoriano-Habit et al. (2024).

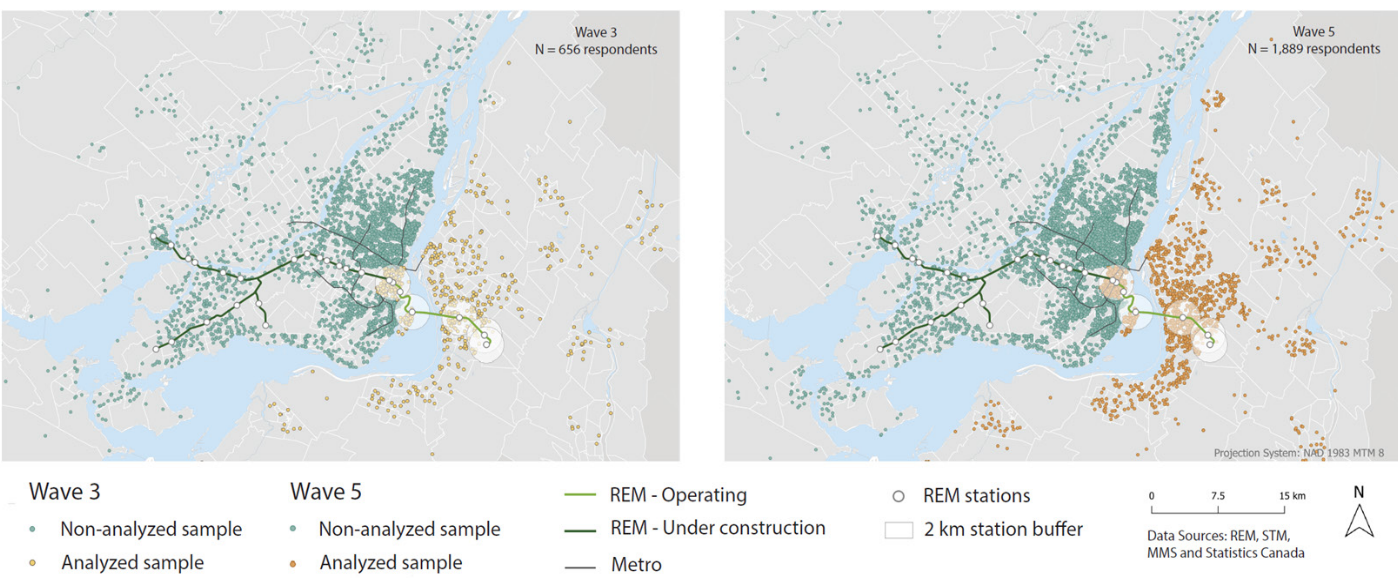


Figure 3.2 Distribution of respondents in the cross-sectional survey

4 Methods

4.1 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, accounting for shared variance (Hair et al., 2014). In this study, we apply EFA to reduce the number of attitudinal and behavioral characteristics evaluated individually while minimizing information loss, allowing for a more structured input for the subsequent clustering analysis. The variables analyzed include perceptions towards the REM and public transport in general, perceptions about gentrification, attitudes towards residential selection, travel behavior in childhood, and current use of transport modes. All questions regarding attitudes and perceptions were asked using a 5-point Likert scale. Weekly frequency of mode usage for active modes, driving, and public transit was reported by respondents for the last 7 days.

We conduct a principal components exploratory factor analysis separately for each survey wave using the psych and factoextra packages in R, based on Pearson correlation matrices. The number of retained factors is determined using both the latent root criterion (eigenvalues ≥ 1) and parallel analysis, which has shown to provide more accurate results than scree plots in determining the number of components (Zwick & Velicer, 1986). Scree plots were also tested to validate the suggested number of factors. To enhance interpretability and minimize cross-loadings, we use varimax rotation as recommended by Hair et al. (2014). Only variables with factor loadings greater than or equal to 0.5 are retained to ensure all variables meaningfully contribute to their respective factors given our sample sizes. Prior to conducting the factor analyses, the factorability of the data is confirmed through multiple diagnostics: each variable was found to correlate at $r \geq 0.3$ with at least one variable, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeded the 0.7 threshold, and Barlett's Test of Sphericity was statistically significant, confirming that the correlation matrix was not an identity matrix.

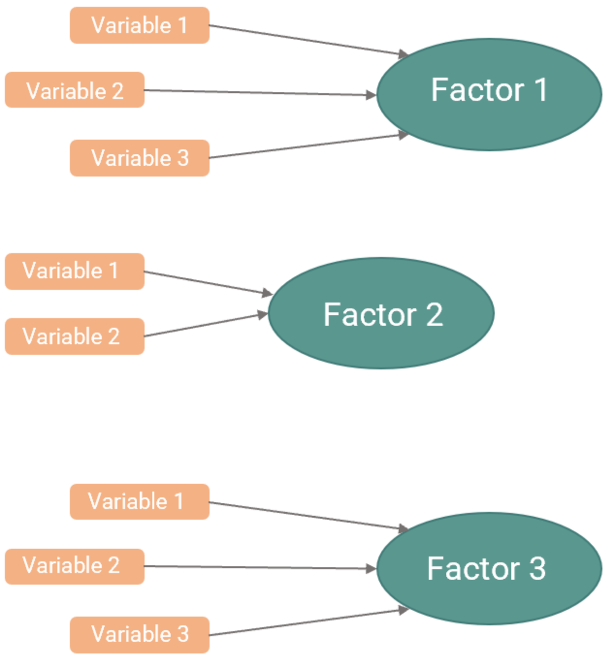


Figure 4.1 Simplified EFA structure

4.2 K-means clustering

K-means clustering is a widely used method for grouping individuals into distinct segments based on how similar their responses are across selected variables. The method works by assigning individuals to clusters and then iteratively updating the average values, called centroids, of each group. This process continues until the within-cluster similarity is maximized and the between-cluster variation is sufficiently distinct. This technique has been widely applied in transport research and shown to be an effective tool for transit market segmentation (Carvalho & El-Geneidy, 2024; Krizek & El-Geneidy, 2007; Van Lierop & El-Geneidy, 2017). For instance, Jacques et al. (2013) and Grise and El-Geneidy (2018) have used it to identify user types based on mode preferences and satisfaction, while Dent et al. (2021) and Cheng et al. (2017) have demonstrated its relevance in evolving transport contexts. Viallard et al. (2019) further highlighted its capacity to capture nuanced behavioral patterns in multimodal environments. To identify user clusters within the REM transit market, we used the factor scores derived from the EFA as primary inputs. The final selection was guided by transit-specific criteria previously established in the literature, including interpretability and policy relevance, as outlined by Krizek and El-Geneidy (2007), later applied by Van Lierop and El-Geneidy (2017) and recently by Carvalho and El-Geneidy (2024). We assessed each clustering solution based on the statistical characteristics of the resulting segments, their relevance to public transit planning, and their alignment with existing research. In addition, we conducted a silhouette analysis to determine the optimal number of clusters, serving as a complementary method to support the selection process.

Clustering was conducted separately for Wave 3 and Wave 5 to capture meaningful shifts in user and non-user segmentation before and after the opening of the REM. By combining both attitudinal and behavioral indicators, the clusters offer a comprehensive view of how transit users and non-users

4.3 Longitudinal analysis

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 Wave 3 to their post-REM cluster in Wave 5, we could determine the extent to which stated intentions were realized as actual usage or whether preferences shifted in unforeseen ways. To account for potential sampling variations, the longitudinal sample was weighted, permitting an estimation of how these transitions might look at the broader population level. These weights were calculated by matching the share of cluster memberships in the longitudinal sample to the shares in the entire cross-sectional sample. The anesrake R package was used for this purpose. Additionally, the same factor-clustering procedure that was done with the cross-sectional sample was repeated with the sample of 181 panel participants. This analysis returned consistent results with no significant differences to the cross-sectional analysis. This, in addition to the use of weights, confirms the reliability of the longitudinal analysis of individual trajectories. This longitudinal approach reveals key patterns, such as the proportion of individuals switching market segments, as well as those who remain entrenched in their preferences.

4.4 Analyzing shifts in the transit market

To better understand the impacts of the REM on travel patterns, a deeper analysis is performed. This analysis focuses on the difference between respondents in wave 3 (2022) and wave 5 (2024) of the MMS. Respondents in the 2024 data are categorized into frequent, infrequent, and non-users based on their self-reported usage of the REM. Respondents who used the REM more than once per month were considered frequent users; those who used it once a month or less were classified as infrequent users; and those who had never used it were considered non-users. This categorization allows analyzing the intended (2022) and actual usage (2024) of the REM across different market segments. This analysis looks deeper into the previously found clusters and reveals both the early impacts of the infrastructure and the behavioral complexities associated with shifting travel patterns. It also highlights which user types were most responsive to the new service and which segments remained disengaged, offering valuable insights for targeted policy interventions and service improvements.

5 Results

5.1 Exploratory factor analysis

The resulting attitudinal and behavioral factors provide a coherent and simplified representation of respondents' attitudes and perceptions. In the 2022 sample, four factors emerged (Table 5.1), capturing a range of perceptions and values: support for the REM, concerns about gentrification, residential location preferences, and childhood travel behavior. These dimensions revealed both forward-looking attitudes and deeper mobility-related experiences, offering a nuanced foundation for segmenting the transit market prior to the REM's opening.

Table 5.1 Factor loadings for the wave 3 (2022) sample of survey respondents

Factor	Variable	Loadings	Cronbach Alpha
REM perception	The REM will be a good thing for the Greater Montréal area.	0.698	0.829
	The REM will be a good thing for my neighborhood.	0.594	
	The REM will be good for Montréal's culture and heritage.	0.750	
	The REM will be good for the environment.	0.681	
	The REM will be good for businesses.	0.819	
Gentrification concerns	I am concerned about whether I will be able to remain in my neighborhood because of rising costs.	0.726	0.694
	I am concerned about whether I will be able to remain in my neighborhood due to rising housing costs with the REM operational.	0.737	
Residential preferences	Being near shops and services was an important factor in my decision to move into my current home.	0.605	0.618
	Being near public transportation was an important factor in my decision to move into my current home.	0.717	
Childhood travel behavior	As a child, I regularly took public transit.	0.701	0.604
	As a child, I was regularly driven around. *	0.630	

Variance Explain. (53.4%); KMO (0.75); Bartlett's Test of Sphericity (χ^2 = 1760.303, d.f. = 55, p-value=0)

*Inverted scale to ensure factor consistency

In the 2024 data sample (Table 5.2), the structure shifted slightly. While the factors related to REM perception, residential preferences, and childhood travel behavior remained consistent, gentrification concerns did not load strongly enough to be retained as a factor. Instead, a new factor reflecting car access, driving behavior, and preferences for automobile-oriented neighborhoods was identified. This shift suggests a possible evolution in how respondents frame their mobility needs and priorities in a post-REM context, which is also a post-pandemic context. The resulting factors in both years were used as core inputs for the clustering analysis, enabling the identification of user groups shaped by both enduring attitudes and evolving travel behaviors. Similar levels of explained variance were observed across both waves, supporting the stability of the factors structure over time and enabling meaningful comparison between the pre- and post-REM survey periods.

Table 5.2 Factor loadings for the wave 5 (2024) sample of survey respondents

Factor	Variable	Loadings	Cronbach Alpha
REM perception	The REM will be a good thing for the Greater Montréal area.	0.805	0.789
	The REM will be good for the environment.	0.737	
	The REM will be good for businesses.	0.732	
	The REM is well integrated in the public transit network in Montréal.	0.510	
	I would recommend the public transport services in the Greater Montréal area to a member of my family or friend.	0.517	
Childhood travel behavior	As a child, I regularly took public transit.	0.561	0.503
	As a child, I was regularly driven around. *	0.589	
Residential preferences	Being near shops and services was an important factor in my decision to move into my current home.	0.698	0.677
	Being near public transportation was an important factor in my decision to move into my current home.	0.667	
	Being in a neighborhood where it is a pleasant to walk was an important factor in my decision to move into my current home.	0.562	
Car and family oriented	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.	0.592	0.543
	I have regular access to at least one private automobile in my household.	0.673	
	Higher share of driving compared to other modes (Dummy)	0.693	

Variance Explain. (39.7%); KMO (0.76); Bartlett's Test of Sphericity (χ^2 = 5445.12, d.f. = 105, p-value=0)

*Inverted scale to ensure factor consistency

5.2 K-means clustering

For each survey wave, the clustering included the factors found through the EFA. For Wave 3 (2022): REM perception, gentrification concerns, residential preferences, and childhood travel behavior. In contrast, the Wave 5 (2024) clustering replaced gentrification concerns with a new factor labeled car and family oriented, which reflects automobile access, driving behavior, and preferences for car-friendly residential environments. The gentrification variable in the 2024 data sample did not meet the factor loading threshold and was instead included as independent a variable in the clustering process.

In addition to the factor scores, we included four independent variables that did not load strongly onto any factor but were deemed important for capturing behavioral dynamics relevant to REM ridership. These include: (1) intention to use the REM, derived from a 5-point Likert scale and recoded as a binary Yes/No variable; (2) telecommuting frequency, defined as the number of days respondents worked remotely in the past week; (3) public transit share, calculated as the number of times transit was used in the last seven days; and (4) driving frequency, calculated the same way.

Clusters of four and five groups were identified as providing the best representation of the REM transit market in the 2022 and 2024 data samples, which can be observed in figures 5.3 and 5.4, respectively. Clusters were named based on the prevalence of attitudes, behaviors, and socio-demographic characteristics observed in each group. Tables 5.5 and 5.6 present the descriptive statistics for the clusters identified in the 2022 and 2024 data samples, corresponding to the four- and five-cluster solutions, respectively. Each table includes key variables related to socio-demographics, travel behavior, and transit-related attitudes. These include household

Figure 5.3 K-means cluster analysis 2022 market – Intention towards the REM

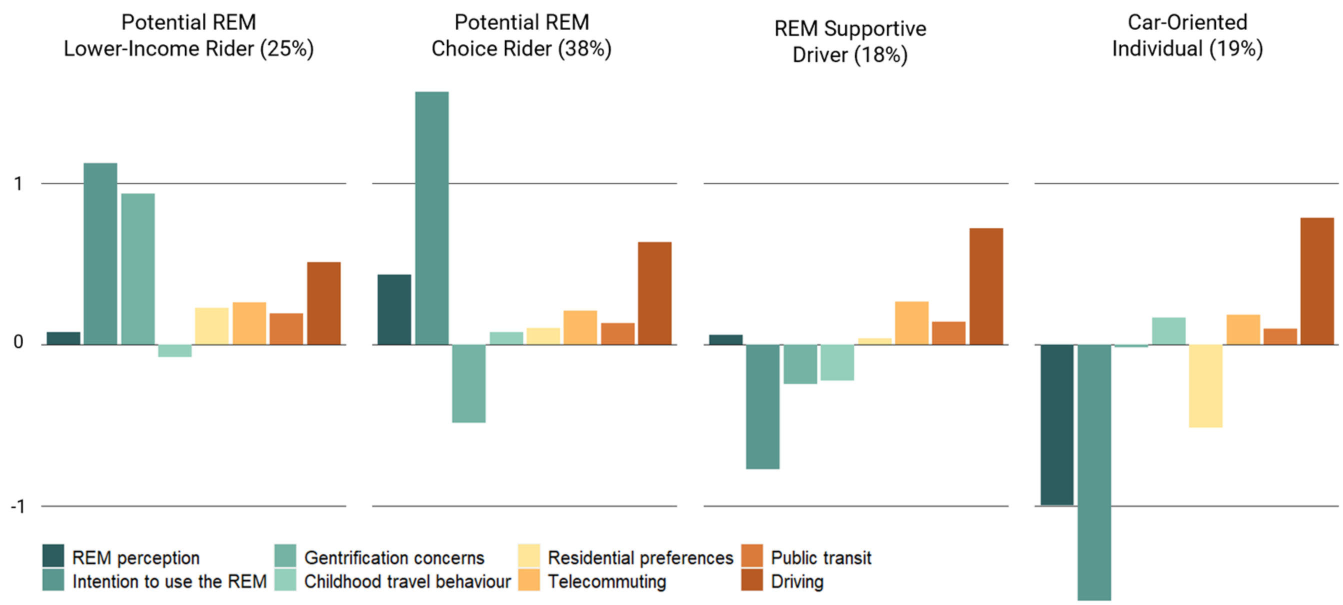
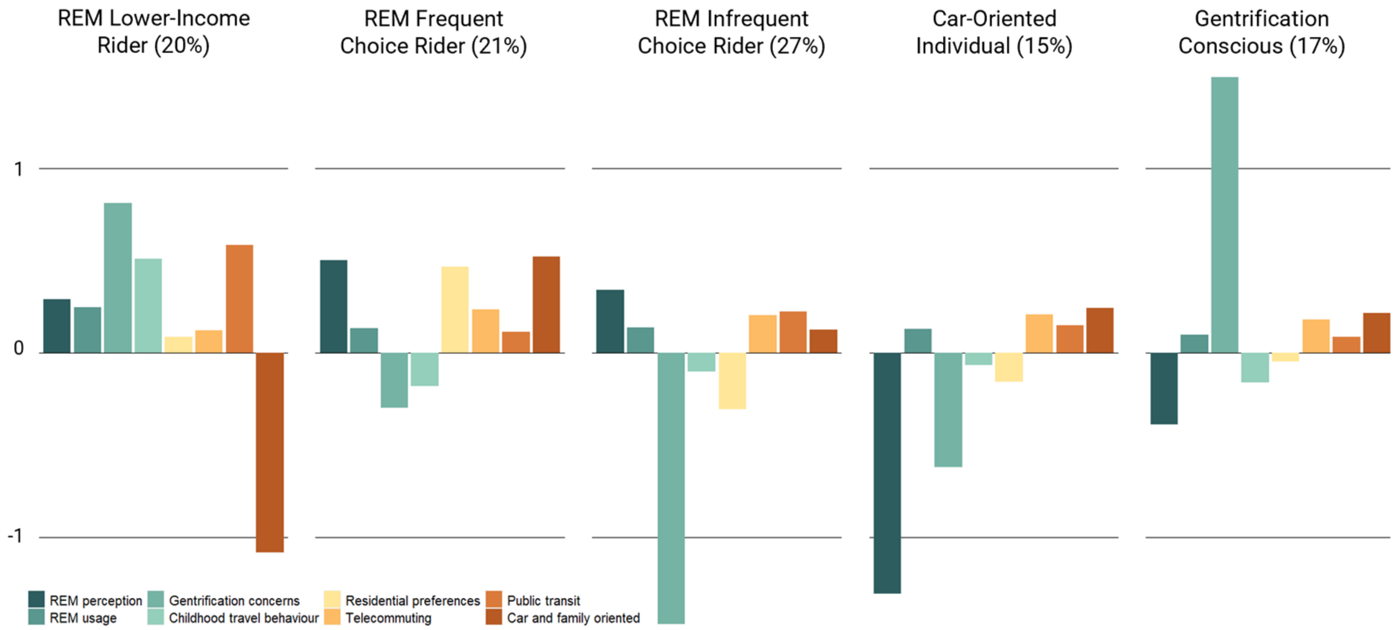


Figure 5.4 K-means cluster analysis 2024 market – Actual use of the REM



The main distinction between the two sets of clusters lies in the intended REM use in 2022 and actual REM use in 2024. Some clusters are present across both samples, such as REM-supportive and car-oriented users, while others are unique to a single period. A detailed description of the four pre-REM profiles and five post-REM profiles are discussed in detail in the following sections.

Table 5.5 Descriptive statistics of the wave 3 (2022) sample by cluster

Variable	Clusters: Potential REM Lower-Income Rider	Potential REM Choice Rider	REM Supportive Driver	Car-Oriented Individual	Wave 3 sample
Sample share	**25%**	**38%**	**18%**	**19%**	100%
Total N	155	236	115	122	628
Sociodemographic characteristics					
Gender					
Female	41.3%	33.1%	40.9%	39.3%	37.7%
Male	58.7%	66.9%	59.1%	60.7%	62.3%
Age					
18-35	23.9%	19.1%	19.1%	7.4%	18.0%
36-59	45.8%	40.7%	49.6%	49.2%	45.2%
60 and over	30.3%	40.3%	31.3%	43.4%	36.8%
Income [in CAD]					
Below 60 k	28.4%	21.2%	23.5%	27.0%	24.5%
60 k-120 k	51.6%	34.7%	42.6%	41.8%	41.7%
Over 120 k	20.0%	44.1%	33.9%	31.1%	33.8%
Distance to REM [in km]	5.5 (6.8)*	6.7 (7.3)*	9.2 (7.9)*	11.2 (8.6)*	7.7 (7.8)*
Access to at least one private automobile [per household]	74 (44)*	86 (35)*	84 (36)*	91 (29)*	84 (37)*
Telecommuting frequency [over 7 days]	1.8 (2.4)*	1.5 (2.1)*	1.8 (2.2)*	1.3 (2)*	1.6 (2.2)*
Perception of transit					
Recommending public transportation service in your region**					
Yes	64.5%	64.4%	42.6%	32.0%	56.8%
No	35.5%	35.6%	57.4%	68.0%	43.2%
Support for REM being positive for Greater Montreal**					
Yes	86.50%	97.30%	89.60%	52.50%	84.40%
No	13.50%	2.97%	10.40%	47.50%	15.60%

** Neutral was considered as a No.

* Mean (Standard Deviation).

Table 5.6 Descriptive statistics of the wave 5 (2024) sample by cluster

Variable	Clusters: REM Lower-Income Rider	REM Frequent Choice Rider	REM Infrequent Choice Rider	Car-Oriented Individual	Gentrification Conscious	Wave 5 sample
Sample share	**20%**	**21%**	**29%**	**14%**	**17%**	100%
Total N	336	352	461	246	286	1681
Sociodemographic characteristics						
Gender						
Female	58.3%	52.3%	40.8%	54.9%	58.7%	51.8%
Male	41.7%	47.7%	59.2%	45.1%	41.3%	48.2%
Age						
18-35	53.9%	22.7%	28.6%	24.0%	38.5%	33.4%
36-59	30.0%	47.2%	44.7%	49.6%	42.0%	42.5%
60 and over	16.1%	30.1%	26.7%	26.4%	19.6%	24.0%
Income [in CAD]						
Below 60 k	31.8%	10.8%	10.6%	12.2%	21.3%	17.0%
60 k-120 k	44.3%	40.1%	36.4%	39.4%	45.1%	40.7%
Over 120 k	23.8%	49.1%	52.9%	48.4%	33.6%	42.4%
Distance to REM [in km]	3.8 (4.6)*	6.9 (7.1)*	8.5 (7.8)*	9.5 (8.7)*	7.3 (7.2)*	7.2 (7.4)*
Access to at least one private automobile [per household]	32 (47)*	98 (14)*	85 (35)*	95 (22)*	95 (22)*	80 (40)*
Telecommuting frequency [over 7 days]	0.9 (1.6)*	1.7 (2.1)*	1.4 (2)*	1.5 (1.9)*	1.3 (1.9)*	1.3 (1.9)*
Perception of transit						
Recommend public transport service in Greater Montreal**						
Yes	92.3%	92.5%	88.8%	45.1%	70.40%	80.8%
No	7.7%	7.5%	11.2%	54.9%	29.6%	19.2%
Support for REM being positive for Greater Montreal**						
Yes	92.0%	99.7%	96.1%	30.9%	72.7%	82.5%
No	8.0%	0.3%	3.9%	69.1%	27.3%	17.5%

** Neutral was considered as a No.

* Mean (Standard Deviation).

5.3 Pre-REM clusters

Potential REM Lower-Income Rider

The Potential REM Lower-Income Rider cluster, represents approximately a quarter of the sample. The cluster is primarily characterized by its comparatively lower socioeconomic status relative to other identified groups. Individuals in this cluster exhibit more limited access to private vehicles, which shapes their transport choices and reliance on alternative modes. This profile demonstrates considerable support for the REM, while expressing a strong intention to use it. Interestingly, their intended use primarily targets recreational and leisure-oriented trips rather than regular commuting. Their existing travel patterns show moderate usage of public transit and active transport modes, reflecting both their economic constraints and the practicalities of their daily mobility.

Potential REM Choice Rider

The Potential REM Choice Rider group constitutes the largest segment identified, accounting for approximately 38% of the sample. It is characterized by relatively high household incomes, with a significant proportion of riders earning over $120,000 annually. Individuals within this group have considerable access to private vehicles, reflecting a lifestyle with multiple transport choices. Despite their car access, this profile displays the strongest overall support for the REM and expresses the highest intention to use the system, both for commuting and leisure-oriented trips. Members of this cluster typically reside within moderate proximity to REM stations, suggesting ease of potential access. However, their current travel patterns reveal continued reliance on driving as the predominant mode, indicating that their favorable views toward the REM coexist with car-oriented behavior. This cluster highlights an important market opportunity for the REM, where positive perceptions and high intentions may translate into selective but meaningful transit usage, particularly if supported by strategies aimed at convenience and seamless integration with their daily travel needs.

REM Supportive Driver

The REM Supportive Driver cluster makes up about 18% of the sample and presents a notable contrast between perceptions and travel intentions. Individuals in this group generally express positive attitudes toward the REM, recognizing its potential benefits for the broader community. However, despite their favorable views, they display limited intentions to adopt the REM themselves. Members of this group have relatively high household incomes and strong access to private vehicles, reflecting their established driving habits and preferences. Additionally, they reside farther from REM stations on average, further diminishing the system's convenience as a transport option. Their existing travel behavior is heavily car-oriented, underscoring a deep-rooted reliance on personal vehicles and limited motivation to shift toward public transit. This cluster represents a segment whose ideological support for public transit investment does not directly translate into personal adoption or behavior change, highlighting a key challenge for promoting modal shifts among entrenched car users.

Car-Oriented Individual

The Car-Oriented Individual cluster, comprising approximately 19% of the sample, represents the most car-dependent group identified. Members of this cluster express the lowest levels of support for the REM and show minimal intention to use the system. This group's profile is characterized by strong automobile reliance, reinforced by the highest rate of access to private vehicles and residence at greater distances from REM stations compared to other clusters. Their travel patterns reflect an overwhelming preference for driving, with minimal engagement in public transit or active transport. Additionally, this group tends to have a higher proportion of older adults, further solidifying traditional car-centric behaviors and preferences. The Car-Oriented Individual profile exemplifies a substantial market challenge, as their entrenched reliance on cars suggests limited openness to transit-oriented alternatives, even with new infrastructure developments.

5.4 Post-REM clusters

REM Lower-Income Rider

In 2024, the REM Lower-Income Rider cluster represented 20% of respondents and maintained its distinguishing characteristic of having the highest share of individuals with lower household incomes compared to other clusters. Members of this group predominantly consisted of younger adults, with more than half aged between 18 and 35, and they were notably more likely to be women (58%). Consistent with their income profile, they continued to have the lowest access to private vehicles among all segments and resided closer to REM stations, facilitating easier system access. Reflecting their practical reliance on transit, this group showed the highest frequency of public transit and active transport usage, with minimal dependence on driving. Their continued support for public transit and the REM underscores this group's critical role in sustaining transit ridership.

REM Frequent Choice Rider

The REM Frequent Choice Rider emerging new cluster, comprising 21% of the sample, is characterized primarily by higher-income respondents with substantial access to private automobiles. Despite that, riders frequently choose to use the REM, demonstrating the system’s strong appeal for both commuting and leisure purposes. Their high REM usage aligns paradoxically with their elevated driving rates and telecommuting frequency, reflecting a lifestyle marked by flexible and diverse transport options. They show exceptionally strong support for the REM, overwhelmingly seeing it as positive for Greater Montréal, indicating their recognition of the system’s broader benefits despite comfortable access to alternative modes.

REM Infrequent Choice Rider

Representing the largest group in 2024 (27%), the REM Infrequent Choice Rider emerging new profile consists mainly of affluent respondents with high levels of car access. Members of this group tend to be middle-aged adults and predominantly men. Although their support for the REM remains notably high, their actual usage of the system is only occasional, suggesting a selective integration of the REM into their routines.

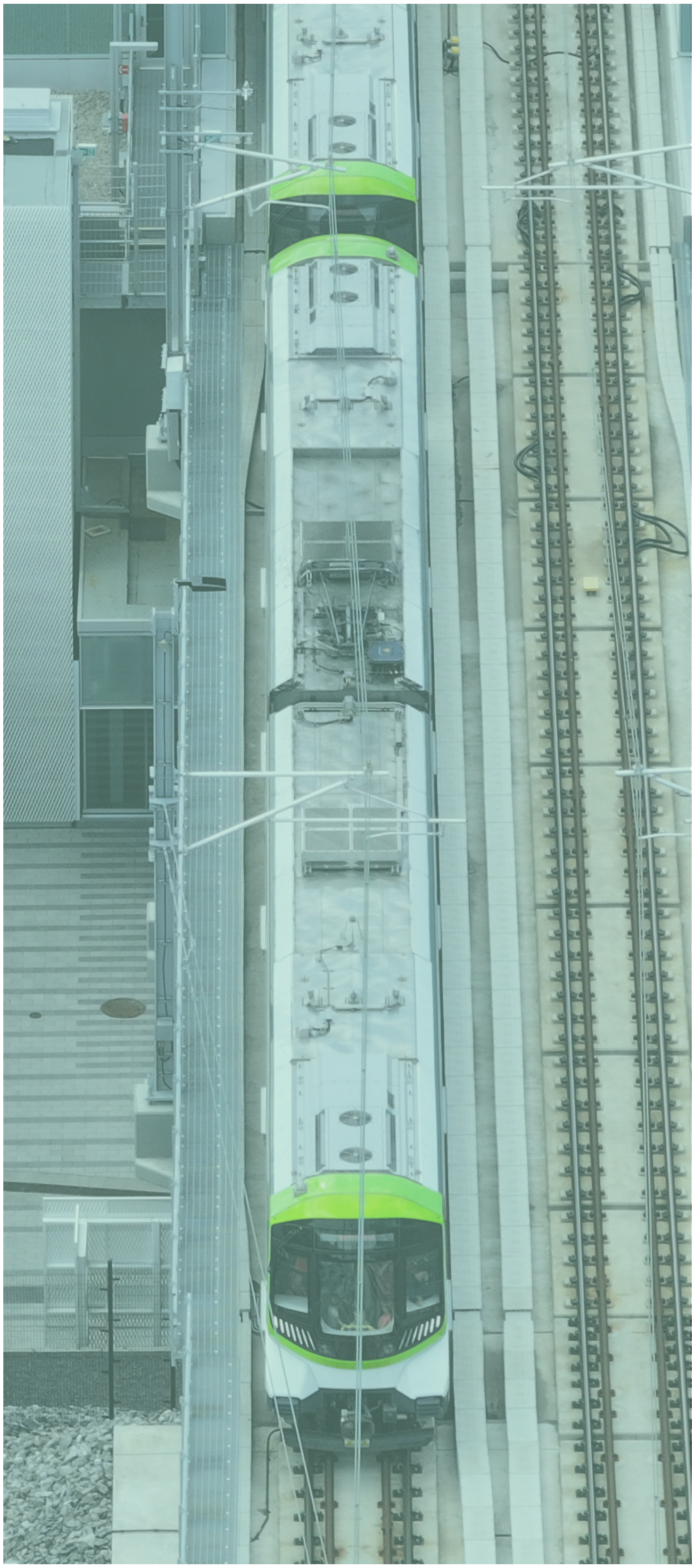
Their overall transport profile is strongly car-dependent, reflecting habitual preferences for driving despite positive perceptions of public

Car-Oriented Individual

In 2024, the Car-Oriented Individual cluster (15%) continues to exhibit strong reliance on personal vehicles, reflecting consistent car-oriented travel behaviors. This segment comprises middle-to-high income households, typically older adults, and is slightly more likely to be women. Members live at greater distances from REM stations and have substantial automobile access, reinforcing their preference for driving as their primary mode of transport.

Gentrification Conscious

Emerging as a distinct group in 2024, the Gentrification Conscious cluster represents 17% of respondents concerned with the potential social impacts associated with the REM's presence. This profile primarily includes middle-income households. Their REM usage patterns are mixed, with roughly a third frequently using the system and an equally large proportion never having used it. Despite moderate use, their support for both public transit and the REM is lower compared to other transit-positive clusters, likely influenced by their concerns about the system's role in neighborhood change, affordability, and displacement risks. This cluster highlights the importance of addressing social equity and community impacts within broader transit planning and policy.

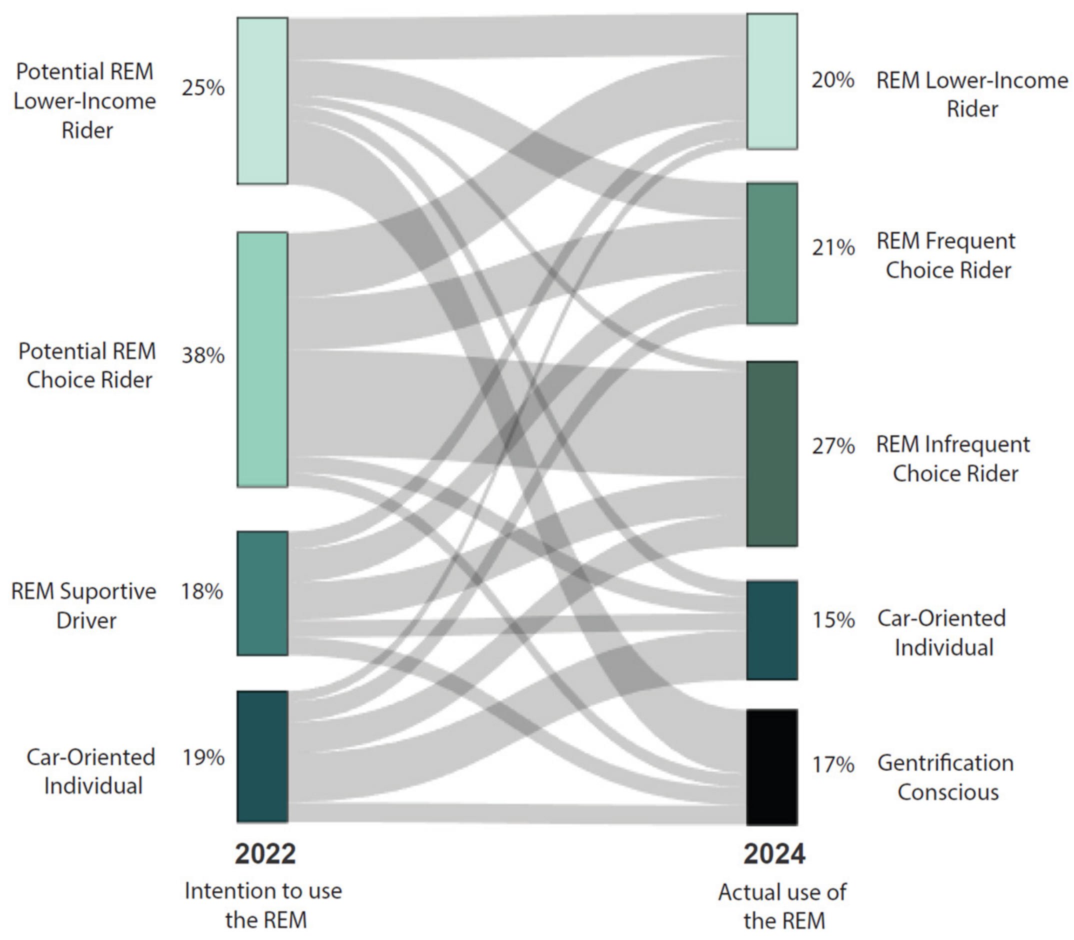


5.5 Longitudinal analysis

The same factor and cluster analysis was conducted for the longitudinal data only and revealed similar patterns to the overall sample from 2022 and 2024. A weighting technique was applied to the longitudinal observation to generate Figure 4 and represents the full sample in term of the identified cluster shares. Figure 5.7 offers a deeper understanding of how individual-level transit behavior and attitudes evolved following the launch of the REM. Tracking respondents who completed both the 2022 and 2024 waves of the survey enabled us to observe how previously stated intentions aligned with or diverged from actual usage over time. This provided insight into the dynamics of modal shift and user adaptation in response to new infrastructure.

A majority of individuals initially classified as Potential REM Choice Riders in 2022 transitioned into the REM Infrequent Choice Rider cluster in 2024. While this group originally expressed high levels of support for the REM and strong intention to adopt it, their eventual usage remained occasional rather than frequent. This suggests that although the REM successfully attracted interest among choice riders, many have yet to fully integrate it into their routines. A smaller portion of this cluster transitioned into the REM Frequent

Figure 5.7 Longitudinal analysis of the REM market



Choice Rider segment, indicating a more sustained pattern of usage, while others moved into the REM Lower-Income Rider cluster. This latter movement may reflect either economic changes or a greater reliance on public transit due to evolving personal or contextual circumstances.

A notable shift was observed among individuals formerly classified as REM Supportive Drivers. In 2022, this segment was defined by positive attitudes toward the REM, but with a stated preference for continued automobile use. By 2024, a significant share of this group had transitioned into both the REM Infrequent and REM Frequent Choice Rider segments. This change points to a meaningful behavioral shift. Individuals who were initially unlikely to use the REM began incorporating it into their mobility patterns once the system became operational. The diversity in their new segment assignments suggests a range of engagement, from occasional or trial-based use to more consistent and purpose-driven adoption.

Although Car-Oriented Individuals remained largely stable in their travel preferences, a portion of this group also migrated toward REM-using segments in 2024. The fact that these respondents previously characterized by low support and intent to use public transit adopted the REM, even on a limited basis, highlights the infrastructure's potential to influence even the most car-dependent users. While this shift was less pronounced than those observed in other clusters, it signals the possibility of gradual behavioral change when supported by improvements in accessibility, service quality, and connectivity.

These transitions between clusters highlight the need to examine not just aggregate shifts but also the behavioral dynamics at the individual level. The longitudinal analysis reveals patterns of both stability and transformation in public transit engagement. Understanding these dynamics is essential for informing transit policy and maximizing the long-term impacts of large-scale infrastructure investments. Importantly, while individuals moved between clusters, the defining characteristics of the clusters themselves remained relatively stable over time. For instance, the Potential REM Choice Rider segment was split into more nuanced subgroups in 2024 due to richer behavioral data, but the underlying profile persisted. This finding suggests that transit agencies can rely on early market segmentation to anticipate user responses and plan accordingly. While individual behavior may evolve with increased experience and contextual changes, the broader market structures appear durable, reinforcing the value of pre-implementation studies in guiding long-term infrastructure planning.

5.6 Shifts in transit market

The introduction of the REM represents a significant investment in public transit infrastructure aimed at improving regional connectivity and encouraging a modal shift toward public transport. Analyzing the intended and actual usage of the REM across different market segments reveals both the early impacts of this infrastructure and the behavioral complexities associated with shifting travel patterns. The results, illustrated in Figure 5.8, highlight varying degrees of alignment between stated intentions in 2022 and observed ridership behaviors in 2024, with evidence of both consistency and divergence across user groups.

Car-Oriented Individuals are a particularly noteworthy case. Despite being the segment with the lowest intention to use the REM prior to its opening, this group reported higher-than-expected levels of usage one year after the system became operational. While they still exhibit the highest share of automobile usage overall, both frequent and infrequent REM usage increased relative to what their initial responses suggested. In parallel, the driving mode share among this group declined between waves, pointing to a partial but measurable modal shift. This finding highlights that even among users with deep-rooted car dependency, there is potential for behavioral adaptation when new

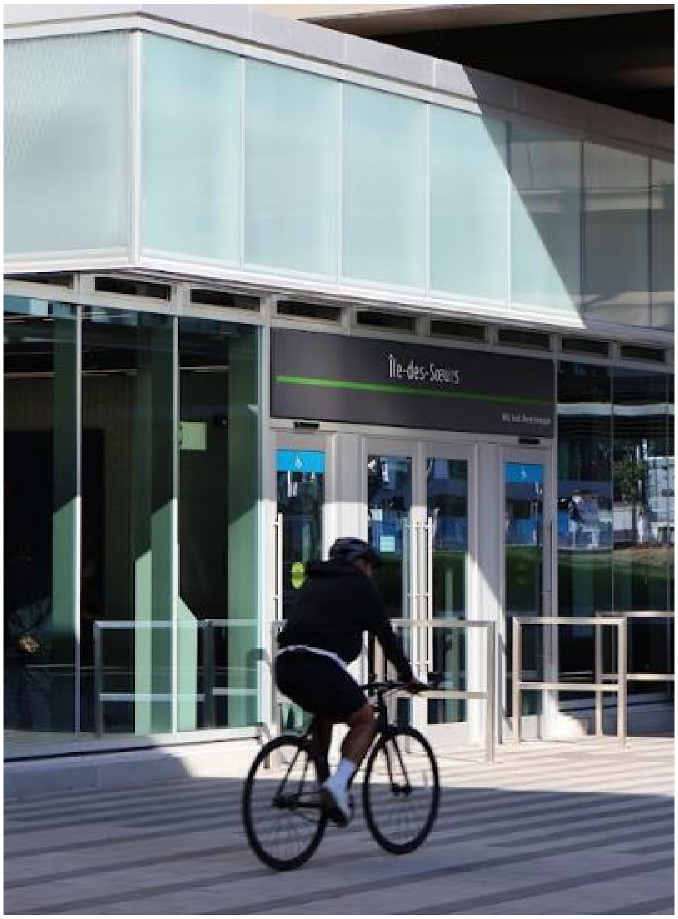
Figure 5.8 Changes in REM adoption and travel behavior across segments

Across the entire sample, the purpose of REM travel remained largely focused on recreation and leisure, both before and after its launch. Work-related travel, while present, was consistently secondary across all user profiles. This suggests that, in its early operational phase, the REM has been adopted more readily as a supplementary mode rather than as a core component of daily commuting routines. Profiles such as the REM Infrequent Choice Riders and Gentrification-Conscious users, in particular, continue to use the REM occasionally, often tied to leisure-oriented or discretionary travel rather than routine employment-related trips.

These findings suggest that while high intention and positive perception of the REM existed prior to its implementation, frequent adoption did not materialize uniformly across groups. This gap between intention and behavior reflects broader challenges in encouraging sustained modal shift, which might be related to the COVID-19 pandemic effects and how behaviour has changed. Factors such as ongoing car ownership, lack of integration with local transit options, limited REM service coverage beyond its first operational phase, and the availability of convenient parking likely continue to reinforce private vehicle use, particularly for work-based travel.

Importantly, the REM does appear to have succeeded in attracting new riders. Both lower-income segments and certain initially car-dependent users demonstrated meaningful shifts in travel behavior. However, the patterns observed suggest that the REM is currently functioning primarily as an auxiliary mode, particularly during off-peak periods and for non-work travel. This trend may persist unless broader strategies are employed to reposition the REM as a viable everyday commuting option.

These insights underscore the need for policy and planning interventions aimed at enhancing REM integration within the wider mobility network. Measures such as increased off-peak frequency, better multimodal connectivity, and expanded first- and last-mile access through active and feeder transport options will be essential to deepen adoption and move beyond leisure-based ridership. Future infrastructure extensions and service refinements should be evaluated with attention to how different user segments adopt and sustain use over time.



6 Discussion and Conclusion

This study contributes to the growing body of literature on public transit market segmentation and behavioral change in response to major infrastructure investments (Brown et al., 2019; Dent et al., 2021; Fu & Juan, 2017; Sanjust et al., 2015) by examining users of the REM in Montréal. By using both cross-sectional and longitudinal data, we identified how people's attitudes and behaviors towards transit evolved over time, particularly as users transitioned between intention and adoption in the context of a new light rail system.

6.1 Gap between attitude and behavior

A primary key takeaway is the observed behavioral transition among initially car-oriented respondents. Many of these individuals, particularly those who had expressed positive attitudes toward the REM but low intent to adopt it in 2022, reported occasional or even frequent REM usage by 2024. This trend indicates that exposure to infrastructure and service availability can prompt changes in travel behavior over time, particularly when supportive attitudes are already present. Such findings align with previous research that emphasizes the role of perceived service quality, convenience, and network integration in shaping transit adoption decisions (Beirão & C., 2007; Schwanen & Mokhtarian, 2005). Targeting groups already inclined to shift modes, even if they remain car users, can be a promising and efficient policy approach.

However, our analysis also reveals a persistent disconnection between stated support for transit infrastructure and actual use. While many respondents expressed strong support for the REM and recognized its benefits for Montréal's Greater Metropolitan area, this did not consistently translate into regular ridership for them. This gap suggests that favorable opinions alone are not sufficient to produce modal shift. Structural barriers such as limited geographic coverage, weak first-mile/last-mile connectivity, lifestyle and habits related to private vehicle ownership continue to constrain adoption, particularly among choice riders. These findings underscore the need for policies that go beyond awareness campaigns or attitudinal shifts and instead focus on tangible improvements to access, service reliability, and network integration (Currie & Delbosc, 2011).

6.2 Equity and gentrification concerns

A primary key takeaway is the observed behavioral transition among initially car-oriented respondents. Many of these individuals, particularly those who had expressed positive attitudes toward the REM but low intent to adopt it in 2022, reported occasional or even frequent REM usage by 2024. This trend indicates that exposure to infrastructure and service availability can prompt changes in travel behavior over time, particularly when supportive attitudes are already present. Such findings align with previous research that emphasizes the role of perceived service quality, convenience, and network integration in shaping transit adoption decisions (Beirão & C., 2007; Schwanen & Mokhtarian, 2005). Targeting groups already inclined to shift modes, even if they remain car users, can be a promising and efficient policy approach.

However, our analysis also reveals a persistent disconnection between stated support for transit infrastructure and actual use. While many respondents expressed strong support for the REM and recognized its benefits for Montréal's Greater Metropolitan area, this did not consistently translate into regular ridership for them. This gap suggests that favorable opinions alone are not sufficient to produce modal shift. Structural barriers such as limited geographic coverage, weak first-mile/last-mile connectivity, lifestyle and habits related to private vehicle ownership continue to constrain adoption, particularly among choice riders. These findings underscore the need for policies that go beyond awareness campaigns or attitudinal shifts and instead focus on tangible improvements to access, service reliability, and network integration (Currie & Delbosc, 2011).

6.3 Leisure use and off-peak demand

To add, the data suggest a clear mismatch between the REM's intended purpose and actual use. Although the system was designed as a primary commuting solution, especially for workers traveling to and from downtown Montréal, ridership patterns indicate that it is frequently used for leisure and recreational purposes, as a complementary purpose. This is consistent across clusters, regardless of income, age, or access to private vehicles. These findings point to an opportunity for planners to recalibrate their service models to reflect emerging demand trends. Rather than focusing solely on peak-hour commuting, the REM could expand its relevance and reach by improving service during evenings, weekends, and around major recreational events. Increasing frequency during non-commute hours, coordinating with feeder bus schedules, and enhancing active transport access to stations could help capture this latent demand and improve overall system efficiency (Park et al., 2021).

6.4 Shifting user segments over time

Finally, our findings suggest that while user profiles remained relatively stable between 2022 and 2024 at an aggregate level, the composition within these clusters shifted significantly at an individual level. These internal shifts reflect a constantly evolving landscape of user needs and mobility experiences, despite apparently stable patterns at an aggregate level. In this way, this research highlights the potential of combining cross-sectional and longitudinal analyses in understanding public transit adoption. While static market segmentation provides insight into user profiles at a given moment, it does not capture the behavioral evolution that occurs as people adjust to new infrastructure over time. The longitudinal analysis revealed subtle but important transitions across segments, demonstrating how users adapt, shift, and renegotiate their travel choices in response to external changes. This approach adds depth to transport planning research by linking stated intention with revealed behavior, providing a more complete picture of how new systems are received and used in practice (Van Lierop & El-Geneidy, 2017). Even so, the overall stability in cluster profiles over time suggests that transit agencies can still rely on early market segmentation to anticipate user responses and plan accordingly.

Conclusion

In sum, this study has shown that the early operational period of Montréal's new LRT has generated both new ridership and new user dynamics, while also revealing critical gaps between planning assumptions and actual behavior. It also highlights the importance of user segmentation as a planning tool, while demonstrating its limitations when applied only at a single point in time. While early segmentation can inform strategic decisions before launch, behavioral patterns evolve, and individuals move across categories in ways that static snapshots cannot capture. Longitudinal approaches, therefore, offer critical insights for anticipating demand, designing services, and identifying gaps in equity and accessibility. This study has certain limitations that present opportunities for future research. While the findings may be generalizable to other public transit systems in the Global North, cities with less consolidated or less frequent networks may not exhibit similar behavioral responses. Furthermore, the two-wave structure of the Montréal Mobility Survey captures an early but relatively short post-launch period. Studies with extended timelines, ideally covering three or more waves, would be better positioned to assess gradual behavioral shifts, long-term retention, and the delayed impacts of infrastructure investments.

Specifically with the REM, future research should revisit this analysis once the full network is in service, especially as connections to the airport and the West Island become operational. The full integration of these segments may significantly alter usage patterns, accessibility perceptions, and public attitudes. Additionally, deeper exploration of the attitudinal and behavioral groups identified here, particularly those concerned with affordability and displacement, would clarify the conditions needed for sustained transit adoption. As urban regions continue to expand transit networks in response to climate, equity, and mobility goals, these insights are essential for ensuring that large-scale investments translate into meaningful, lasting changes in travel behavior.

References

Allen, J., Eboli, L., Forciniti, C., Mazzulla, G., & Ortúzar, J. (2019). The role of critical incidents and involvement in transit satisfaction and loyalty. Transport policy, 75, 57-69. https://doi.org/10.1016/j.tranpol.2019.01.005

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. Transportation Research Part A: Policy and Practice, 192, 104376. https://doi.org/https://doi.org/10.1016/j.tra.2025.104376

Anable, J. (2005). 'Complacent Car Addicts' or 'Aspiring Environmentalists'? Identifying travel behaviour segments using attitude theory. Transport policy, 12(1), 65-78.

Beimborn, E., Greenwald, M., & Jin, X. (2003). Accessibility, connectivity, and captivity: Impacts on transit choice. Transportation Research Record: Journal of the Transportation Research Board, 1835(1), 1-9. https://doi.org/10.3141/1835-01

Beimborn, E. A., Greenwald, M. J., & Jin, X. (2003). Accessibility, Connectivity, and Captivity: Impacts on Transit Choice. Transportation Research Record: Journal of the Transportation Research Board, 1835(1), 1-9. https://doi.org/10.3141/1835-01

Beirão, G., & C., S. (2007). Understanding attitudes towards public transport and private car: A qualitative study. Transport policy, 14(6), 478-489. https://doi.org/10.1016/j.tranpol.2007.04.009

Brough, R., Freedman, M., & Phillips, D. C. (2021). Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. J Reg Sci, 61(4), 753-774. https://doi.org/10.1111/jors.12527

Brown, B., Jensen, W., & Tharp, D. (2019). Residents' expectations for new rail stops: optimistic neighborhood perceptions relate to subsequent transit ridership. Analyses of Social Issues and Public Policy, 3(1), 139-160.

Cao, X., & Schoner, J. (2014). The influence of light rail transit on transit use: An exploration of station area residents along the Hiawatha line in Minneapolis. Transportation Research Part A: Policy and Practice, 59, 134-143.

Carvalho, T., & El-Geneidy, A. (2024). Everything has changed: the impacts of the COVID-19 pandemic on the transit market in Montréal, Canada. Transportation, 1-24. https://doi.org/10.1007/s11116-024-10497-2

Casello, J., Towns, W., Belanger, J., & Kassiedass, S. (2015). Public Engagement in Public Transportation Projects: Challenges and Recommendations. Transportation research record, 2537(1), 88-95.

Chen, H. (2015). Structural interrelationships of group service quality, customer satisfaction, and behavioral intention for bus passengers. International Journal of Sustainable Transportation, 10(5), 418-429. https://doi.org/10.1080/15568318.2014.965372

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. Transportation research record, 2671(1), 10-19.

Currie, G., & Delbosc, A. (2011). Understanding bus rapid transit route ridership drivers: An empirical study of Australian BRT systems. Transport policy, 18(5), 755-764. https://doi.org/10.1016/j.tranpol.2011.03.003

Currie, G., & Wallis, I. (2008). Effective ways to grow urban bus markets – a synthesis of evidence. Journal of Transport Geography, 16(6), 419-429. https://doi.org/10.1016/j.jtrangeo.2008.04.007

Damant-Sirois, G., & El-Geneidy, A. (2015). Who cycles more? Determining cycling frequency through a segmentation approach in Montreal, Canada. Transportation Research Part A: Policy and Practice, 77, 113-125.

Damant-Sirois, G., Grimsrud, M., & El-Geneidy, A. (2014). What's your type: A multidimensional cyclist typology. Transportation, 41, 1153-1169.

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. Transportation Research Record, 2675(10), 1043-1054. https://doi.org/https://doi.org/10.1177/03611981211014528

Dillman, D., Smyth, J., & Christian, L. (2014). Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method, Wiley.

Eldeeb, G., & Mohamed, M. (2020). Quantifying preference heterogeneity in transit service desired quality using a latent class choice model. Transportation Research Part A: Policy and Practice, 139, 119-133. https://doi.org/10.1016/j.tra.2020.07.006

Fu, X., & Juan, Z. (2017). Drivers of transit service loyalty considering heterogeneity between user segments. Transportation Planning and Technology, 40(5), 611-623.

Grise, E., & El-Geneidy, A. (2018). Where is the happy transit rider? Evaluating satisfaction with regional rail service using a spatial segmentation approach. Transportation Research Part A: Policy and Practice, 114, 84-96.

Grube-Cavers, A., & Patterson, Z. (2014). Urban rapid rail transit and gentrification in Canadian urban centres: A survival analysis approach. Urban Studies, 52(1), 178-194. https://doi.org/10.1177/0042098014524287

Guerra, E. (2022). What the heck is a choice rider? A theoretical framework and empirical model. Journal of Transport and Land Use, 15(1). https://doi.org/10.5198/jtlu.2022.2096

Haider, M., & Anwar, A. (2022). The prevalence of telework under Covid-19 in Canada. Information Technology & People, 36(1), 196-223. https://doi.org/10.1108/itp-08-2021-0585

Hair, J., Black, W., Babin, B., & Anderson, R. (2014). Multivariate data Analysis (7 ed.). Prentice Hall.

Jacques, C., Manaugh, K., & El-Geneidy, A. (2013). Rescuing the captive [mode] user: an alternative approach to transport market segmentation. Transportation, 40(3), 625-645. https://doi.org/10.1007/s11116-012-9437-2

Jamal, S., Newbold, B., & Scott, D. (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, 54(4), 870-884.

Kim, S., & Ulfarsson, G. (2012). Commitment to light rail transit patronage: Case study for St. Louis MetroLink. Journal of Urban Planning and Development, 138(3), 227-234. https://doi.org/https://doi.org/10.1061/(ASCE)UP.1943-5444.0000115

Krizek, K., & El-Geneidy, A. (2007). Segmenting preferences and habits of transit users and non-users. Journal of public transportation, 10(3), 71-94. https://doi.org/https://doi.org/10.5038/2375-0901.10.3.5

Legrain, A., Buliung, R., & El-Geneidy, A. (2019). Who, what, when, and where: Revisiting the influences of transit mode share. Transportation Research Record: Journal of the Transportation Research Board, 2537(1), 42-51. https://doi.org/10.3141/2537-05

Manaugh, K., Badami, M., & El-Geneidy, A. (2015). Integrating social equity into urban transportation planning: A critical evaluation of equity objectives and measures in transportation plans in North America. Transport policy, 37, 167-176. https://doi.org/10.1016/j.tranpol.2014.09.013

Mesbah, M., Sahraei, M., Soltanpour, A., & Habibian, M. (2022). Perceived service quality based on passenger and trip characteristics: A structural equation modeling approach. Journal of Rail Transport Planning & Management, 23. https://doi.org/10.1016/j.jrtpm.2022.100340

Moniruzzaman, M., & Páez, A. (2012). Accessibility to transit, by transit, and mode share: application of a logistic model with spatial filters. Journal of Transport Geography, 24, 198-205. https://doi.org/10.1016/j.jtrangeo.2012.02.006

Owen, A., & Levinson, D. (2015). Modeling the commute mode share of transit using continuous accessibility to jobs. Transportation Research Part A: Policy and Practice, 74, 110-122. https://doi.org/10.1016/j.tra.2015.02.002

Palm, M., Allen, J., Zhang, Y., Tiznado-Aitken, I., Batomen, B., Farber, S., & Widener, M. (2022). Facing the future of transit ridership: shifting attitudes towards public transit and auto ownership among transit riders during COVID-19. Transportation (Amst), 1-27. https://doi.org/10.1007/s11116-022-10344-2

Pan, M., & Ryan, A. (2023). Segmenting the target audience for transportation demand management programs: An investigation between mode shift and individual characteristics. International Journal of Sustainable Transportation, 18(1), 62-83. https://doi.org/10.1080/15568318.2023.2201941

Park, K., Farb, A., & Chen, S. (2021). First-/last-mile experience matters: The influence of the built environment on satisfaction and loyalty among public transit riders. Transport policy, 112, 32-42. https://doi.org/10.1016/j.tranpol.2021.08.003

Sanjust, B., Meloni, I., & Spissu, E. (2015). An impact assessment of a travel behavior change program: A case study of a light rail service in Cagliari, Italy. Case Studies on Transport Policy, 3(1), 12-22.

Schwanen, T., & Mokhtarian, P. (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods? Journal of Transport Geography, 13(1), 83-99. https://doi.org/10.1016/j.jtrangeo.2004.11.001

Van Lierop, D., & El-Geneidy, A. (2017). A new market segmentation approach: Evidence from two Canadian cities. Journal of public transportation, 20(1), 20-43. https://doi.org/https://doi.org/10.5038/2375-0901.20.1.2

Viallard, A., Trépanier, M., & Morency, C. (2019). Assessing the evolution of transit user behavior from smart card data. Transportation Research Record: Journal of the Transportation Research Board, 2673(4), 184-194. https://doi.org/10.1177/0361198119834561

Victoriano-Habit, R., & El-Geneidy, A. (2024). Studying the interrelationship between telecommuting during COVID-19, residential local accessibility, and active travel: a panel study in Montréal, Canada. Transportation, 51(3), 1149-1166.

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.

Wang, X., Yan, X., Zhao, X., & Cao, Z. (2022). Identifying latent shared mobility preference segments in low-income communities: Ride-hailing, fixed-route bus, and mobility-on-demand transit. Travel Behaviour and Society, 26, 134-142. https://doi.org/10.1016/j.tbs.2021.09.011

Zhao, J., Webb, V., & Shah, P. (2014). Customer Loyalty Differences between Captive and Choice Transit Riders. Transportation research record, 2415(1), 80-88.

Zuk, M., Bierbaum, A., Chapple, K., Gorska, K., & Loukaitou-Sideris, A. (2017). Gentrification, displacement, and the role of public investment. Journal of Planning Literature, 33(1), 31-44. https://doi.org/10.1177/0885412217716439

Zwick, W., & Velicer, W. (1986). Comparison of Five Rules for Determining the Number of Components to Retain. Psychological bulletin, 99(3), 432-442.

McGill