COMPARATIVE ANALYSIS OF USER CHOICE BEHAVIOR IN CARSHARING SERVICES: A CASE STUDY IN MONTRÉAL, CANADA

1. INTRODUCTION

Carsharing systems provide an alternative to private car ownership by allowing users to pay a subscription fee and per-use charge, thus mitigating fixed ownership expenses (Shaheen et al., 1998). These systems operate on a shared-use principle, where users access vehicles on-demand rather than owning them (Ciari et al., 2016). Carsharing is particularly appealing to individuals without personal vehicles who require flexible transport options when public transit is less convenient. Additionally, users may opt for other shared mobility services, such as bicycles or scooters, depending on travel distance and conditions.

Understanding user preferences is crucial for carsharing operators, as it enables service optimization through demand-based fleet distribution and operational adjustments. Carsharing has seen significant global expansion, growing from 600 cities in 18 countries in 2007 (Shaheen & Cohen, 2007) to over 3,000 cities in 50 countries by 2019 (Kuhn, Marquardt, & Selinka, 2021). Station-based carsharing remains dominant, though free-floating models continue expanding. Examples of providers include Flinkster, Zipcar, and Stadtmobil for station-based services; Share Now, Witcar, and E-Car for free-floating models; and Communauto and Getaround for both services.

Behavioral models highlight several factors influencing carsharing adoption, including convenience, flexibility, and cost (Acheampong & Siiba, 2019). Perceived service quality and flexibility make carsharing an attractive alternative, particularly free-floating car-sharing (FFCS), which has been shown to reduce private car ownership while integrating with public transport for mixed-use mobility (Becker et al., 2018).

Studies suggest that increasing cost for private car travel and parking promote carsharing (Li & Kamargianni, 2020). Attitudinal factors play a critical role in such decisions, with instrumental (e.g., time savings, cost-effectiveness) and affective (e.g., freedom, pleasure) motivations affecting adoption at different cognitive stages (Yu et al., 2023; Jain et al., 2020). Socioeconomic characteristics also influence usage; younger, higher-income, and better-educated individuals in dense urban areas are more likely to use carsharing (Li & Zhang, 2021; García et al., 2022). Car ownership and gender significantly impact willingness to adopt, with high private car ownership areas posing challenges for carsharing promotion (Xu et al., 2023).

Station availability and location also influence adoption; increased vehicle supply at stations boosts rentals, but station placement in commercial areas may be less effective on non-workdays (Abbasi et al., 2019). Regular long-distance travelers show lower carsharing propensity (De Luca & Di Pace, 2014), but familiarity with the service increases the likelihood of use (Xu et al., 2023; Abbasi et al., 2019). Pricing strategies are crucial once higher costs and lower perceived savings reduce membership duration and usage (Costain et al., 2011; Giorgione & Viti, 2023). Additionally, users consider reservation options, parking availability, and access convenience, with competition between FFCS and public transport and cycling (Carrone et al., 2020). Land-use also factors influence station-based carsharing, particularly within an 800-meter radius, while long-term members are more consistent users (Habib et al., 2011).

In this paper, we examine the factors influencing user choices between Free-Float Car Sharing (FFCS) and Station-Based Car Sharing (SBCS) using data from Communauto in Montréal, Canada. A Binomial Logit Model and sensitivity analysis are applied to assess how cost, accessibility, and demographics affect decision-making. Communauto provides both FFCS – where users pick up and drop off vehicles within a designated area – and SBCS, which operates through pre-established stations.

2. METHODS

The proposed methodology consists of five steps. First, data selection and treatment identify relevant attributes affecting users' choices, including proximity to stations, cost, convenience, vehicle availability, and demographics. Unlike many studies relying on stated preferences, this research emphasizes observed choices using a comprehensive dataset of actual trips. Second, a data treatment procedure filters relevant attributes and transforms trips into choice probabilities.

The next step of the method comprises the estimation of binary Logit models considering the attributes affecting the choice between FFCS and SBCS, given their effectiveness in transportation research for modeling discrete choice behavior (Train, 2009). All variables are included in the first model, and only statistically significant variables are retained to obtain the final model. Finally, the results are analyzed, followed by a fifth step where a sensitivity analysis evaluates how changes in cost influence the choice probability of each alternative.

3. CASE STUDY

3.1 Dataset

The study assesses Montréal's car-sharing system using data from Communauto, covering approximately 220,000 trips from September 2022. The dataset includes trip details (start and end times, distance, price, and vehicle availability within 250–750 meters) and user demographics (age, subscription date, residence, and gender). After filtering out incomplete records and outliers, the final dataset consisted of 3,145 users engaging with both station-based and free-floating car-sharing services.

Six key regions were identified in the city characterized by strong transportation infrastructure and multimodal mobility options: Le Plateau-Mont-Royal – a high-density, walkable neighborhood with strong transit and cycling infrastructure, attracting students and professionals; Rosemont-La Petite-Patrie – an area with strong public transit, bike paths, and mixed residential-commercial spaces; Ville-Marie–Laurier–Sainte-Marie –central district with high-density mixed-use spaces and strong mobility options; Mercier–Hochelaga-Maisonneuve – community-focused, transit-accessible neighborhood with affordable housing; and Villeray–Saint-Michel–Parc-Extension –multicultural, transit-oriented area with a mix of rental and family housing.

The data treatment involved multiple steps to refine and preprocess the dataset. Initially, records with missing values for age, region of residence, or subscription date were removed. Only users who engaged with both Free-Floating Car Sharing (FFCS) and Station-Based Car Sharing (SBCS) were retained while those using only one system were not considered, and outliers were excluded using boxplot analyses.

Key travel attributes such as average traveled distance, price, trip duration, vehicle availability, and average pickup distance were then computed for each system. To quantify system preference, the proportion of trips taken with each system per individual was calculated, and a binary variable was assigned based on the system with the highest proportion of trips. Finally, a logarithmic transformation was applied for data normalization, specifically to attributes like trip duration and vehicle availability.

3.2 Models

An initial binary Logit model for carsharing choices in Montréal was estimated using Biogeme (Bierlaire, 2003), incorporating the attributes: fare per kilometer (FEE_DISTANCE; CAD/km); trip duration (DURATION; minutes); availability by the number of vehicles available (AVAILABILITY); pick-up distance (DISTANCE; meters); age (AGE); period of subscription (SUBSCRIPTION); gender (GENDER); and region where the trip started (REGION). Through an iterative process, attributes with non-significant parameters were removed, resulting in the following final model retaining only significant parameters at a 10% significance:

$$\begin{aligned} V_{FF} = {} & \beta_{FEE\_DISTANCE} * FEE\_DISTANCE\_FF + \beta_{DURATION} * DURATION\_FF + \beta_{AVAILABILITY\_FF} * \\ & AVAILABILITY\_FF + \beta_{PICKUP\_FF} * PICKUP\_FF + \beta_{AGE\_31\_45} * AGE\_31\_45 + \beta_{AGE\_46\_MORE} * \\ & AGE\_46\_MORE + \beta_{SUBSCRIPTION} * SUBSCRIPTION + \beta_{GENDER} * GENDER + \beta_{REGION\_1} * \\ & REGION\_1 + \beta_{REGION\_2} * REGION\_2 + \beta_{REGION\_3} * REGION\_3 + \beta_{REGION\_4} * REGION\_4 + \\ & \beta_{REGION\_5} * REGION\_5 + \beta_{REGION\_6} * REGION\_6 \end{aligned} \tag{1}$$

$$\begin{aligned} V_{SB} = {} & ASC_{SB} + \beta_{FEE\_DISTANCE} * FEE\_DISTANCE\_SB + \beta_{DURATION} * DURATION\_SB + \\ & \beta_{AVAILABILITY\_SB} * AVAILABILITY\_SB + \beta_{PICKUP\_SB} * PICKUP\_SB \end{aligned} \tag{2}$$

where V_{FF} and V_{SB}: utility of FFCS; ASC_{SB}: Alternative Specific Constant for SBCS; $\beta_{FEE\_DISTANCE}$: parameter for fee per distance; $\beta_{DURATION}$: parameter for trip duration; $\beta_{AVAILABILITY\_FF}$ and $\beta_{AVAILABILITY\_SB}$: parameters for availability; β_{PICKUP_FF} and β_{PICKUP_SB}: parameters for pickup distance; $\beta_{AGE\_31\_45}$ and $\beta_{AGE\_46\_MORE}$: parameters for age; $\beta_{SUBSCRIPTION}$: parameter for subscription time; β_{GENDER}: parameter for gender; and β_{REGION_1}, β_{REGION_2}, β_{REGION_3}, β_{REGION_4}, β_{REGION_5} and β_{REGION_6}: parameters for region.

3.3 Results and discussion

Table 1 displays the model estimation results from the fourth methodological step, comparing the initial model with all attributes and the final model ("Region_1" and "Age_46 or More" are reference categories). The initial model suggests that pickup distance for free-floating (FFCS) systems and choice in region 6 significantly impact alternative choices at a 10% significance level. Meanwhile, the station-based (SBCS) alternative-specific constant, fee per distance, trip duration, FFCS vehicle availability, being under 46 years old, and choices in regions 2 and 4 significantly influence choices at a 5% level. Other variables, including SBCS availability, pickup distance for both systems, subscription time, gender, and choices in regions 3 and 5, are not significant.

Table 1 - Estimates of the initial and final models

	Initial model				Final model			
	Value	Rob. Std err	Rob. t-test	Rob. p-value	Value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_SB	-0.070*	0.263	-0.267	0.039	-0.286*	0.220	-1.300	0.002
FEE_DISTANCE	-0.527*	0.062	-8.470	0.000	-0.523*	0.062	-8.420	0.000
DURATION	0.159*	0.035	4.530	0.000	0.156*	0.035	4.460	0.000
AVAILABILITY_FF	0.366*	0.077	4.780	0.000	0.391*	0.073	5.340	0.000
AVAILABILTIY_SB	-0.021	0.013	-1.600	0.110	-	-	-	-
PICKUP_DISTANCE_FF	-0.001**	0.000	-1.700	0.089	-0.001**	0.000	-1.620	0.105
PICKUP_DISTANCE_SB	-0.000	0.000	-1.450	0.148	-	-	-	-
AGE_19_30	0.544*	0.122	4.440	0.000	0.591*	0.114	5.190	0.000
AGE_31_45	0.368*	0.104	3.540	0.000	0.392*	0.102	3.840	0.000
SUBSCRIPTION	-0.014	0.016	-0.870	0.384	-	-	-	-
GENDER	0.065	0.077	0.841	0.400	-	-	-	-
REGION_2	0.272*	0.119	2.300	0.022	0.211*	0.105	2.000	0.045
REGION_3	0.127	0.140	0.913	0.361	-	-	-	-
REGION_4	0.307*	0.157	1.960	0.050	0.244**	0.146	1.670	0.095
REGION_5	0.115	0.139	0.829	0.407	-	-	-	-
REGION_6	0.208**	0.114	1.820	0.068	0.123	0.097	1.260	0.206
	Initial Model				**Final Model**			
Initial log-likelihood	-2179.95				-2179.95			
Final log-likelihood	-1957.18				-1960.78			
Rho-square	0.09				0.10			

* significant at 5%; ** significant at 10%

The final model confirms that SBCS availability, pickup distance for SBCS, subscription time, gender, and choices in regions 3 and 5 remain non-significant. However, pickup distance for FFCS and choice in region 6 retain significance at 10%, while the other previously significant factors (SBCS alternative-specific constant, fee per distance, trip duration, FFCS availability, age, and choices in regions 2 and 4) remain significant at 5%.

The negative alternative-specific constant (-0.286) for SBCS indicates that users prefer FFCS over SBCS systems. The negative coefficient for the fee per distance (-0.523) shows that higher costs reduce the likelihood of selecting a system, emphasizing pricing as a key determinant of choice. The decision to use a single beta value across equations was supported by consistent results across hypothesis tests, simplifying the analysis while maintaining result robustness.

A positive coefficient for trip duration (0.156) suggests that users are more likely to choose the system where trip duration is longer, aligning with Logit model predictions. FFCS vehicle availability (0.391) is a key factor, as greater accessibility increases adoption by reducing search time and enhancing convenience, particularly in urban areas. In contrast, SBCS availability became non-significant, likely due to vehicle reservations ensuring availability, thus reducing search concerns. Younger users are more likely to engage with car-sharing, with coefficients of 0.591 (ages 19–30) and 0.392 (ages 31–45), suggesting that younger people have a preference for FFCS. This may be due to lower familiarity, physical limitations, or technological barriers among older individuals.

After sensitivity analysis we identified the breakeven cost per kilometer that impacts user preferences. Users are more likely to choose free-floating car-sharing when the price per kilometer is below 1.5 CAD/km. However, when the cost surpasses this threshold, they tend to prefer station-based systems.

4. CONCLUSIONS

This study analyzes the factors influencing users' choices between free-floating and station-based car-sharing systems. We modeled users' choices using real usage data obtained from a dataset of a car-sharing operator that provides both car-sharing services in Montréal, Canada. Key attributes affecting these choices include vehicle availability, trip duration, price per kilometer, proximity of pick-up points, and sociodemographic factors. General preference for free-floating services is identified, with older users being less likely to use car sharing. Vehicle availability within a 500-meter radius positively influences free-floating car-sharing choices, highlighting the importance of accessibility. Longer trips increase the likelihood of using car-sharing, while higher trip costs reduce it, underscoring price sensitivity.

We tested alternative models, including Log-Normal and Latent Class mixed Logit models, but found no additional insights beyond those obtained with the Logit model. However, the research acknowledges limitations, such as the absence of trip purpose data, which could provide deeper insights into user motivations, route choices, and vehicle usage duration. Additionally, comparing car-sharing with other transport alternatives such as bike-sharing and public transport, could further enhance understanding of users' decision-making.

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