Decaying-memory experience-dependent preferences for route familiarity among shared e-scooter commuters

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Short summary

Examining the route choices of shared e-scooter users allows planners to identify infrastructure priorities, understand emerging mobility patterns, and evaluate the performance of the transportation network. Studies exploring shared e-scooter route choices are, however, limited, especially when compared with bicycle route choice. In fact, no study has explored the habitual route choice behaviour of e-scooter users, for example from those who commute via e-scooter. This study addresses this by first identifying commuters from shared e-scooter GPS trajectory data in Lyon, France, and then analysing their route choice preferences. In particular, through the estimation of novel route familiarity measures, we explore i) whether shared e-scooter commuters have preferences for taking familiar routes, ii) whether preference for familiarity is experience-dependent (i.e. dependent on the travel cost of the route taken), and iii) whether commuters have decaying memory (i.e. whether they care more about recent commutes than older commutes).

Keywords: Shared e-scooter, Route choice, GPS, Commuter, Route familiarity.

1 Introduction

Over the past decade, shared e-scooter services have been extensively introduced in numerous cities across the globe (Li et al., 2022; Mitropoulos et al., 2023). In theory, shared e-scooters could be competitive for short to medium distance trips and become a constituent part of urban mobility (Reck et al., 2021; Manout et al., 2024). However, in practice, the introduction of this service has sparked various problems, particularly related to conflicts over public infrastructure use (Gössling, 2020). Because there is little dedicated infrastructure for e-scooters (both in terms of routes and parking), they frequently compete with other transport modes such as bikes and users of public space, leading to negative outcomes such as e-scooters being ridden on sidewalks or cluttering in shared areas when parked.

Several studies have been conducted in the literature on e-scooter use exploring, for example, user profiles (Gkavra & Susilo, 2026), usage profiles (Li et al., 2022), integration within the urban mobility landscape (Reck et al., 2021; Manout et al., 2024), and service regulation (Gössling, 2020; Hurlet et al., 2024). However, in comparison to shared bicycling, studies on the route choices of shared e-scooter users remains under-researched (Chen et al., 2026). Zuniga-Garcia et al. (2021) found that in the early days of shared e-scooters in Austin, USA, routes were split between sidewalks (18%), bike lanes (11%), and roads (33%). More recently, several studies have shown that people using shared e-scooters tend to favor dedicated cycling infrastructure over other types of routes, even when this requires taking considerable detours to access it (Schumann et al., 2025a; Zhang et al., 2021). Other authors compared routes choice preferences between shared e-scooters and bikes and found that they share preferences for some route characteristics such as crosswalks and stops, and that they differ in tastes/perception for other characteristics, such as cycling lanes, streetlights, car parking places, or safety (Cubells et al., 2023; Ringhand et al., 2024). Chen et al. (2026) showed that e-scooter users do not value all types of cycling infrastructure equally, tending to favor asphalt bike lanes over other surfaces because of the superior riding comfort they offer. Furthermore, several authors found that e-scooter route choice was not only influenced by the

type of infrastructure (for e.g. bike lanes), but also the built-environment surrounding this infrastructure such as blue and green spaces, commercial amenities, or sidewalks (Cubells et al., 2023; Schumann et al., 2025a; Chen et al., 2026).

No study, however, has explored the habitual route choice behaviour of e-scooter users, for example from those who commute via e-scooter. This study addresses this by first identifying regular commuters from shared e-scooter GPS trajectory data, and then analysing their route choice preferences, where we aim to explore: i) whether shared e-scooter commuters have preferences for taking familiar routes, ii) whether preference for familiarity is experience-dependent (i.e. dependent on the travel cost of the route taken), and iii) whether commuters have decaying memory (i.e. whether they care more about recent commutes than older commutes). Numerous studies have explored preferences for route "stickiness" (Kim et al., 2017; Arriagada et al., 2025; Di et al., 2017), but to the best of our knowledge, none have looked at familiarity in terms of route overlap, nor explored experience-dependence or decaying memory.

2 Shared e-scooter commuter identification

Shared e-scooter data

The focus of this study is on analysing the route choices of travellers who regularly commute by shared e-scooter. The route observation data has been collected from GPS trajectories of shared e-scooter trips in Lyon, France. The GPS data covers the period of January 1, 2022, to March 1, 2024, where the user ID is given so that behaviour of an individual can be tracked across multiple days. The GPS trajectories were map-matched to Lyon's road/bicycle network, where the cycling infrastructure information of each network link was obtained from the open source grandlyon data (2026) platform. Table 1 displays the network attributes used for route generation and in the route utility function.

Table 1: Network attributes used in the route choice model

Attribute	Observed use	Unit	Description
No cycling infrastructure	62.60%	[m]	
Protected bicycle tracks	6.56%	[m]	see fig 1a
Painted bicycle lanes	8.41%	[m]	see fig 1b
Painted lane against traffic	5.15%	[m]	see fig 1c
Bus and cycle lane	2.85%	[m]	see fig 1e and fig 1f
Separate off-road cycling track	1.95%	[m]	see fig 1d
Residential roads	12.49%	[m]	Residential roads: OSM tag highway=residential

Rule-based method for determining commuters

Following Kone et al. (2025), commuters were identified using a rule-based method. First, a day of GPS traces for an individual was flagged as a potential commuting day if at least two GPS trajectories were observed that day, and the first points of two GPS trajectories occurred between 6-9am and 3-8pm, respectively. Based on the coordinates of the first and last GPS points of the flagged potential home-to-work and work-to-home commutes, we then performed a spatial clustering using the k-Medoids algorithm to identify home and work point clusters. Home/work locations were approximated as the centroids of the home/work point clusters. An individual with at least two days of both home-to-work and work-to-home trips was then assumed to be a commuter. Fig. 3a and Fig. 3b display an example of the commutes for an individual and their approximated home/work locations. In total, 1,703 users were identified as shared e-scooter commuters, totally 24,142 trips. Fig. 2a displays the distribution of the number of commutes from each individual, Fig. 2b displays the distribution of the departure times of the commutes, and Fig. 2c displays the distribution of the commute distances.

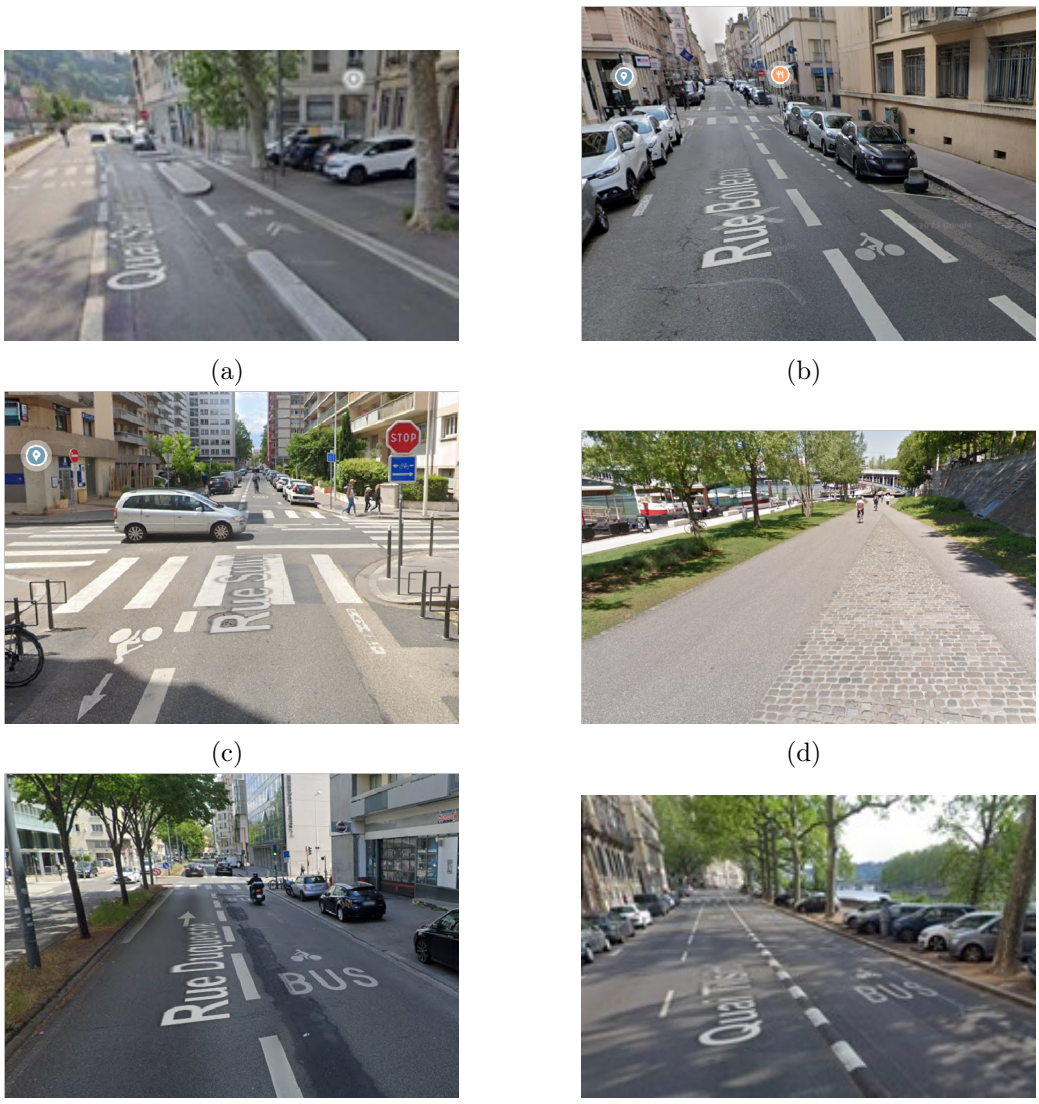


Figure 1: Type of bicycle infrastructure : (a) Protected lane , (b) Painted lane, (c) painted lane against traffic, (d) separate off-road cycling track , and (e,f) bus and cycle lane. Source Google Street View 2025.

3 Route choice model and familiarity measures

Route generation method

To generate route alternatives, we adopted a doubly stochastic method Nielsen (2000). First, we randomly generated 300 weights for each network link, based on the following cost function for link a:

$$V_a = \sum_k (1 + \epsilon_k) X_{a,k} + \varepsilon_a \tag{1}$$

where k are the attributes in Table 1, $X_{a,k}$ is the attribute k value for link a, $\epsilon_k \sim$ truncated normal distribution with mean = 0, std = 1, lower bound = 0, and upper bound = $+\infty$, and $\varepsilon_a \sim$ truncated normal distribution with mean = $\sum_k (1+\varepsilon_k) X_{a,k}$, std = $\sum_k (1+\varepsilon_k) X_{a,k}$, lower bound = 0, and upper bound = $+\infty$.

Based on each of the 300 settings of the link weights, we conducted 300 shortest path searches for each commute route observation. Then, we unified the route choice sets generated for each observed commute from a commuter, so that the route choice set R is the same across commutes. The observed commute routes were paired with the generated route with the greatest overlap.

Observed routes with less than 70% overlap were discarded, which was 18% of observations. After discarding commuters with less than two commutes remaining, as well as according to some other criteria such as commute distance, 831 commuters remained. The average route choice set across commuters was 1092, noting the choice set unification across commutes.

Route choice model

To estimate the dynamic route choices of shared e-scooter commuters, we estimate a Multinomial Logit (MNL) choice model with lagged variables. The probability of choosing route r on commute n is given by:

$$P_{r,n}(\boldsymbol{\beta}, \lambda) = \frac{\exp(V_{r,n}(\boldsymbol{\beta}, \lambda))}{\sum_{s \in R} \exp(V_{s,n}(\boldsymbol{\beta}, \lambda))} \tag{2}$$

where $V_{r,n}(\beta, \lambda)$ is the deterministic utility of route r on commute n, defined as follows:

$$\begin{aligned} V_{r,n}(\boldsymbol{\beta}, \lambda) =& \beta_1 X_{r,1} \left(1 + \sum_{k=2} \beta_k X_{r,k}\right) + \beta_{ID} ID_r + \beta_{PS} \ln(PS_r) \\ &+ \beta_{DF} DF_{r,n}(\lambda) + \beta_{EDF} DEF_{r,n}(\boldsymbol{\beta}, \lambda) + \beta_{F_1} F_{r,1} \end{aligned} \tag{3}$$

$X_{r,1}$ is the total length of route r, and $X_{r,k}$ for $k = 2, ...$ is the proportion of route r that is network attribute k, for the network attributes in Table 1. No cycling infrastructure is chosen as the reference category (β_k=0), so that the other β_k parameters are interpreted as relative dispreferences to the reference category. ID_r is the intersection density of route r measuring the number of intersections passed per km. PS_r is the path size term for route r that measures the distinctiveness of the route (Duncan et al., 2020), so that $\ln(PS_r)$ corrects for route overlap correlations. $DF_{r,n}$, $DEF_{r,n}$, and $F_{r,1}$ are the route familiarity measures that will be described below. Note that route choice preferences are assumed to be constant across time/commutes, i.e. the estimated tastes are not dynamic, but some of the variables are.

First, we define the overlap between route r (on commute n) and the chosen route r_m on commute $m < n$ as:

$$\sigma(r, r_m) = \frac{\sum_{a \in A_r \cap A_{r_m}} l_a}{\sqrt{L_r}\sqrt{L_{r_m}}} \tag{4}$$

where A_r is the set of links in route r, l_a is the length of link a, and L_r is the total length of route r.

The decaying-memory route familiarity measure of route r on commute n is as follows:

$$DF_{r,n}(\lambda) = \sum_{m=2}^{n-1} \lambda^{(n-m)} \sigma(r, r_m) \tag{5}$$

where $0 \leq \lambda \leq 1$. The measure captures the extent to which route r on commute n overlaps with previous routes taken by the commuter on commutes m prior to n. $\lambda = 1$ implies that the commuter cares about all the previous routes they took. $\lambda \to 0$ implies that the commuter cares only about recent commutes (i.e. they have decaying memory). Note that it is particularly relevant to measure familiarity in terms of overlap in the current study as shared e-scooter travellers do not always originate and destinate in the same place. It thus captures whether travellers tend to connect with familiar routes, even when starting or ending in different places.

The decaying-memory experience-dependent route familiarity measure of route r on commute n is as follows:

$$DEF_{r,n}(\boldsymbol{\beta}, \lambda) = \sum_{m=2}^{n-1} \lambda^{(n-m)} \sigma(r, r_m) \overline{V}_{r_m,m}(\boldsymbol{\beta}) \tag{6}$$

where $\overline{V}_{r_m,m}(\boldsymbol{\beta}) = \beta_1 X_{r_m,1} (1 + \sum_{k=2} \beta_k X_{r_m,k}) + \beta_{\text{ID}} ID_{r_m}$ for the chosen route on commute m: r_m. This measure captures whether familiar routes are more likely to be taken when they have lower generalised travelling costs, i.e. higher (less negative) $\overline{V}$.

In order to mitigate "The Initial Condition Problem" of not being certain the first observed commute was the first actually taken, we adopt the method proposed by Woolridge (2020) of including preference for familiarity with the initial observed commute route taken:

$$F_{r,1} = \sigma(r, r_1) \tag{7}$$

4 Estimation results

Table. 2 displays the parameter estimation results. As can be seen from the adjusted ρ^2 metric, the model provides good fit to the data. The parameters are all statistically significant, apart from for bus and cycling lanes and painted lanes. This implies that shared e-scooter commuters do not have preferences for bus and cycling lanes or painted lanes over no cycling infrastructure. They do, however, prefer protected lanes and separated cycling tracks, which makes sense. Note that due to working in "Value of Distance space", a negative parameter estimate for the network attributes implies a less negative dispreference compared to the reference category: $\beta_1(1 + \beta_k)$. The commuters are for example willing to travel 8.2% longer distance to travel on separated cycling tracks than on roads without cycling infrastructure. Some cycling infrastructure attributes are actually dispreferred over no cycling infrastructure, which is perhaps surprising, but a large majority of roads in Lyon have no infrastructure, and e-scooters tend to be used more on pavements/roads than bicycles. This finding is also not uncommon in e-scooter route choice studies. Chen et al. (2026), for example, found that bike lanes did not, on the whole, significantly attract e-scooters riders. Ringhand et al. (2024) also found no significant increase in route choice probability in favour of main roads with dedicated cycling infrastructure. Shared e-scooter commuters in the present study were found though to have a much stronger dispreference to travelling on painted lanes against traffic (+0.149) than with traffic (+0.014). This finding is consistent with that of Schumann et al. (2025b), who found that travelling in the contra-flow direction of a one-way road - whether legally permitted to or not - is consistently associated with lower choice probabilities. We also find here that shared e-scooter commuters have a dispreference for travelling on residential streets, and tend to avoid routes passing many intersections.

In regards to the route familiarity measures, the results make sense: there is a positive preference for route familiarity (+1.220), where the preference for familiarity increases when a lower travelling cost was experienced (+0.997). The positive preference for familiarity is expected given results from previous studies, but it is an interesting finding that preference is experience-dependent. It makes sense: if a bad route choice was made - for example if it was long, did not travel on preferred cycling infrastructure, or passed many intersections - then there is less of an incentive to travel the route / sections of the route again. It is also an interesting finding that the commuters did not have decaying memory ($\lambda = 0.966$), suggesting that commuters care about all of their previous commuting route choices. This aligns with travellers having a positive preference for familiarity with the first observed commute route taken (+6.677).

Table 2: Estimation Results

Parameter	Coefficient	Std. Error	t-stat	p-value
Total route length	−6.665	0.129	−51.477	***
Protected lanes	−0.020	0.040	3.339	***
Separated cycling track	−0.082	0.096	5.653	***
Painted lane	0.014	0.074	−1.249	
Residential street	0.082	0.108	−5.035	***
Painted lanes against traffic	0.149	0.080	−12.420	***
Bus and cycling lanes	−0.011	0.064	1.180	
Path size term	0.323	0.025	12.769	***
Intersection density	−0.148	0.007	−20.134	***
Decaying familiarity	1.220	0.115	10.651	***
Initial condition for familiarity	6.677	0.280	23.824	***
Decaying experience-dependent familiarity	0.997	0.048	20.866	***
lambda (λ)	0.966	0.007	133.760	***
Log-likelihood		-16583.267		
Adjusted ρ^2		0.396		
Total number of observations		5,092		
Number of commuters		831		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Conclusion

This study has, for the first time, explored the habitual route choice behaviour of shared e-scooter commuters. Commuters were identified from shared e-scooter GPS trajectory data, and then novel route familiarity measures were estimated to provide new insights into their habitual choice behaviour. The findings of this study, which reveal experience-dependent and non-decaying preferences for route familiarity, may hold practical value for transportation practitioners. In particular, the trade-off between route familiarity and travel costs in route choice probabilities could be leveraged in the design of route guidance strategies. Future research could investigate heterogeneity in familiarity preferences, including identifying travellers who tend to switch routes frequently, for example due to boredom or repeated unsatisfactory experiences. In a related direction, it would be valuable to examine whether travellers persist in using familiar routes even when superior alternatives are available. Such behavior could highlight the importance of making effective initial route decisions.

Acknowledgements

The authors acknowledge the financial support of the FORBAC project.

References

Arriagada, J., Prato, C., & Munizaga, M. (2025). Incorporating the inertia effect into a route choice model using fare transaction data from a large-scale public transport network. *Transportation Research Part A: Policy and Practice*, *196*, 104467.

Chen, S., Cao, Z., & Zhang, X. (2026, April). Modeling e-scooter route choices: Infrastructural preferences and intervention scenario analysis. *Transportation Research Part A: Policy and Practice*, *206*, 104921. Retrieved from http://dx.doi.org/10.1016/j.tra.2026.104921 doi: 10.1016/j.tra.2026.104921

Cubells, J., Miralles-Guasch, C., & Marquet, O. (2023). E-scooter and bike-share route choice and detours: Modelling the influence of built environment and sociodemographic factors. *Journal of transport geography*, *111*, 103664.

Di, X., Liu, H., Zhu, S., & Levinson, D. (2017). Indifference bands for boundedly rational route switching. *Transportation Research Part A: Policy and Practice*, *44(5)*, 1169-1194.

Duncan, L., Watling, D., Connors, R., Rasmussen, T., & Nielsen, O. (2020). Path size logit route choice models: Issues with current models, a new internally consistent approach, and parameter estimation on a large-scale network with gps data. *Transportation Research Part B: Methodological*, *135*, 1-40.

Gkavra, R., & Susilo, Y. O. (2026). Understanding the e-scooter user puzzle: a systematic literature review. *Transport Reviews*, *46*(1), 52–76.

Gössling, S. (2020, February). Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. *Transportation Research Part D: Transport and Environment*, *79*, 102230. Retrieved from http://dx.doi.org/10.1016/j.trd.2020.102230 doi: 10.1016/j.trd.2020.102230

grandlyon data. (2026, January). *grandlyon data.* Retrieved from http://www.data.grandlyon.com/ ([Online; accessed 7. jan. 2026])

Hurlet, P., Manout, O., & Diallo, A. O. (2024). Policy implications of shared e-scooter parking regulation: an agent-based approach. *Procedia Computer Science*, *238*, 444–451. Retrieved from http://dx.doi.org/10.1016/j.procs.2024.06.046 doi: 10.1016/j.procs.2024.06.046

Kim, J., Corcoran, J., & Papamanolis, M. (2017). Route choice stickiness of public transport passengers: Measuring habitual bus ridership behaviour using smart card data. *Transportation Research Part C: Emerging Technologies*, *83*, 146-164.

Kone, Y., Alimo, P. K., Manout, O., Bouzouina, L., Kourtit, K., & Nijkamp, P. (2025). Using citizen observatory gps data to trace changes in cycling practices: prospects and limitations. *European Transport Research Review*, *17*(1), 63.

Li, A., Zhao, P., Liu, X., Mansourian, A., Axhausen, K. W., & Qu, X. (2022, April). Comprehensive comparison of e-scooter sharing mobility: Evidence from 30 european cities. *Transportation Research Part D: Transport and Environment*, *105*, 103229. Retrieved from `http://dx.doi.org/10.1016/j.trd.2022.103229` doi: 10.1016/j.trd.2022.103229

Manout, O., Diallo, A. O., & Gloriot, T. (2024, November). Implications of pricing and fleet size strategies on shared bikes and e-scooters: a case study from lyon, france. *Transportation*. Retrieved from `http://dx.doi.org/10.1007/s11116-024-10559-5` doi: 10.1007/s11116-024-10559-5

Mitropoulos, L., Stavropoulou, E., Tzouras, P., Karolemeas, C., & Kepaptsoglou, K. (2023, September). E-scooter micromobility systems: Review of attributes and impacts. *Transportation Research Interdisciplinary Perspectives*, *21*, 100888. Retrieved from `http://dx.doi.org/10.1016/j.trip.2023.100888` doi: 10.1016/j.trip.2023.100888

Nielsen, O. (2000). A stochastic transit assignment model considering differences in passengers utility functions. *Transportation Research Part B: Methodological*, *34(5)*, 377-402.

Reck, D. J., Haitao, H., Guidon, S., & Axhausen, K. W. (2021, March). Explaining shared micromobility usage, competition and mode choice by modelling empirical data from zurich, switzerland. *Transportation Research Part C: Emerging Technologies*, *124*, 102947. Retrieved from `http://dx.doi.org/10.1016/j.trc.2020.102947` doi: 10.1016/j.trc.2020.102947

Ringhand, M., Schackmann, D., Anke, J., Porojkow, I., & Petzoldt, T. (2024). Differences in route choice behavior when riding shared e-scooters vs. bicycles – a field study. *Journal of Safety Research*, *89*, 343-353. Retrieved from `https://doi.org/10.1016/j.jsr.2024.04.008` doi: 10.1016/j.jsr.2024.04.008

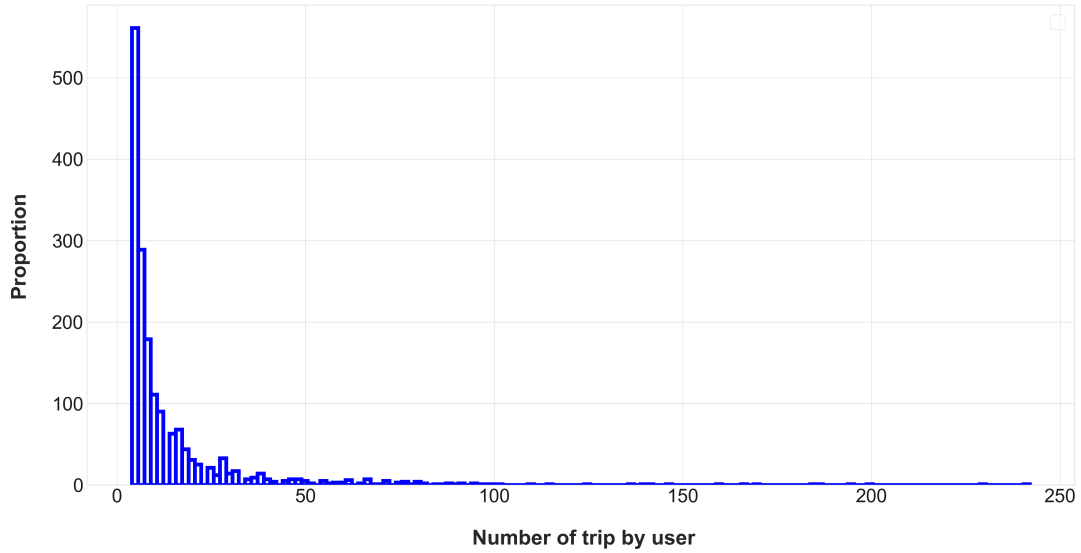
Schumann, H.-H., Haitao, H., Meister, A., Natapov, A., & Quddus, M. (2025a). City-scale gps data reveals impact of spatial configuration and dedicated infrastructure on e-scooter route choice. *Scientific Reports*, *15*(1). Retrieved from `https://doi.org/10.1038/s41598-025-06938-2` doi: 10.1038/s41598-025-06938-2

Schumann, H.-H., Haitao, H., Meister, A., Natapov, A., & Quddus, M. (2025b). City-scale gps data reveals impact of spatial configuration and dedicated infrastructure on e-scooter route choice. *Scientific Reports*, *15*(1), 24175.

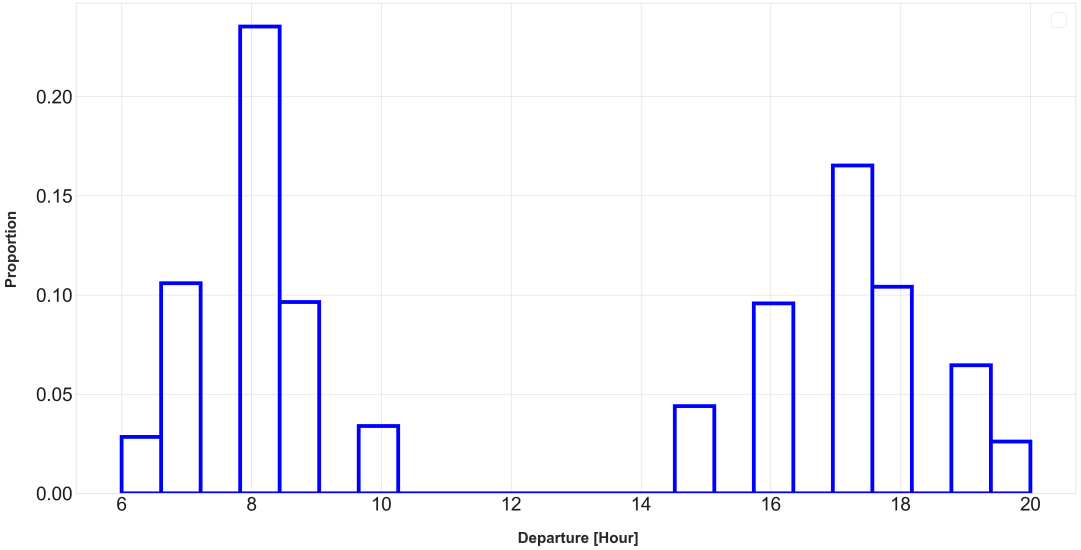
Woolridge, J. (2020). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics*, *20(1)*, 39-54.

Zhang, W., Buehler, R., Broaddus, A., & Sweeney, T. (2021). What type of infrastructures do e-scooter riders prefer? a route choice model. *Transportation Research Part D: Transport and Environment*, *94*, 102761. Retrieved from `https://doi.org/10.1016/j.trd.2021.102761` doi: 10.1016/j.trd.2021.102761

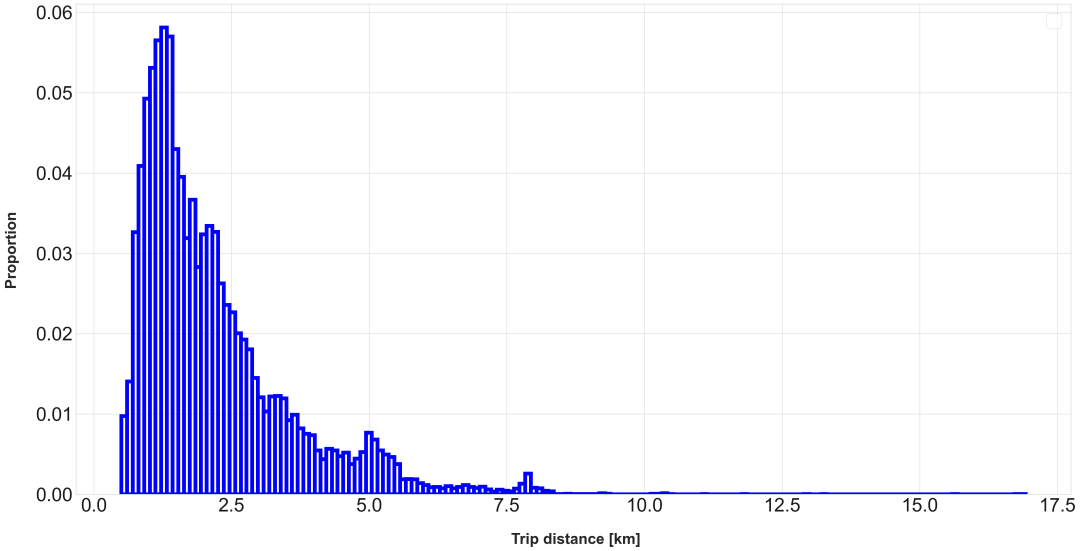
Zuniga-Garcia, N., Ruiz Juri, N., Perrine, K. A., & Machemehl, R. B. (2021). E-scooters in urban infrastructure: Understanding sidewalk, bike lane, and roadway usage from trajectory data. *Case Studies on Transport Policy*, *9*(3), 983-994. Retrieved from `https://doi.org/10.1016/j.cstp.2021.04.004` doi: 10.1016/j.cstp.2021.04.004



(a) Distribution of the number of commutes by the identified commuters in Lyon metropolitan area



(b) Distribution of the departure hours of identified shared e-scooter commuters in Lyon metropolitan area



(c) Distribution of the trip distances of identified shared e-scooter commuters in Lyon metropolitan area

Figure 2: Descriptive information on identified shared e-scooter commuters



(a) Home to work

(b) Work to Home

Figure 3: Plot of GPS trajectories for an identified shared e-scooter commuter, with approximated home and work locations.