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Abstract

In recent years, the emergence of shared mobility services has created new opportunities for more flexible intermodal travel, but the behavioral barriers to their adoption remain poorly understood. Using stated-preference data collected in 2024 in Geneva, Switzerland, we estimate mode-pair-specific pure transfer penalties across public transport, personal bikes, and shared mobility services. A set of itinerary choice models are specified using an assisted algorithm and refined manually to ensure plausibility and consistency with behavioral theory. Results highlight significant variation in perceived transfer disutility, influenced by mode familiarity and user characteristics. These findings contribute to a deeper understanding of intermodal travel behaviors, enabling their integration into simulation models and informing the design of mobility hubs in practice.

Keywords
pure transfer penalty; intermodal travel; discrete-choice experiment; stated preferences

Preferred citation

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1 Introduction

Reducing energy consumption and transitioning to low-emission mobility are key policy objectives in Switzerland and abroad. In recent years, the emergence of shared mobility services—such as car-sharing, bike- and e-bike-sharing, *etc.*—has created new opportunities for more flexible, intermodal travel, particularly when combined with public transport for first- and last-mile connections. While these developments hold promise for more sustainable transport systems, the behavioral mechanisms underlying the adoption and acceptance of such multimodal combinations remain insufficiently understood.

In particular, a central aspect of intermodal travel behavior is the inconvenience associated with switching modes, commonly referred to as the *pure transfer penalty* (PTP). This penalty, usually expressed in *equivalent in-vehicle minutes* (EIVM), captures the additional disutility experienced from making a transfer—beyond any additional walking or waiting time—and has been shown to play a significant role in shaping route and mode choices. Over the past two decades, a growing number of studies have attempted to quantify the PTP in different contexts, typically using discrete choice models estimated on stated (*e.g.*, Espino and Román, 2020; Jara-Diaz *et al.*, 2022) or revealed (*e.g.*, Nielsen *et al.*, 2021; Yap *et al.*, 2024) preference data. Collectively, this body of work has shown that the disutility associated with transfers is context-dependent, and that it can vary widely depending on factors such as transfer infrastructure quality (Guo and Wilson, 2011; Nielsen *et al.*, 2021), the presence of real-time information (Chowdhury *et al.*, 2014; Garcia-Martinez *et al.*, 2018), station crowdedness (Navarrete and Ortúzar, 2013; Garcia-Martinez *et al.*, 2018), weather conditions (Jara-Diaz *et al.*, 2022), time of the day (Kapitza, 2024), trip purpose (Espino and Román, 2020), or the degree of physical integration between modes (Yap *et al.*, 2024).

However, despite these insights, most existing studies remain focused on traditional public transport modes—typically between buses and metro—without accounting for individual modes; in particular, to the best of our knowledge, no study has yet provided empirical estimates of mode-pair-specific PTP values that include transfers to or from personal bikes or shared mobility services. As a result, little is known about how these modes are perceived within the context of intermodal trips, or how they might be integrated more effectively into the public transport network to encourage sustainable mobility.

This work contributes to addressing that gap by investigating how transfer penalties vary across a range of mode combinations, with a particular focus on those involving active and shared mobility. Using data from a stated-preference route-choice survey conducted in

Geneva, Switzerland, in 2024, we present a series of binary logit models generated through an assisted specification algorithm (Ortelli *et al.*, 2021; Bierlaire and Ortelli, 2023) and subsequently refined manually to include random agent effects. Our findings are broadly consistent with values reported in the existing literature and provide new evidence on PTP values of transfers involving emerging modes across different traveler segments, while also underscoring the need for additional data to improve the precision of these estimates.

The remainder of this paper is organized as follows: in the next section, we describe the design and deployment of the stated-preference survey; Section 3 presents our modeling approach and discusses the obtained results; finally, Section 4 summarizes the main findings of this study.

2 Survey design and data collection

The data used in this study were collected between October and November 2024 through an online survey conducted in Geneva, Switzerland. The questionnaire was designed to gather detailed information on individuals' use of shared mobility services and their experience with intermodal travel. It covered the following dimensions:

- Awareness, access to, and frequency of use of car-sharing and bike-sharing;
- Descriptions of the respondent's most recent intermodal trips involving (i) bike-sharing, (ii) car-sharing, and (iii) public transportation only, including information on duration, purpose, mode combinations, and reasons for choosing shared mobility;
- Socioeconomic characteristics, including ownership of private vehicles, e-bikes, *etc.*;
- A discrete-choice experiment focused on intermodal route choice.

The discrete choice experiment consisted of three binary route-choice scenarios per respondent. In each scenario, participants chose between two alternative travel options: one direct and one involving a transfer. The alternatives varied along several attributes, including the modes and the in-vehicle time (IVT) of each trip leg, as well as walking and waiting times associated with the transfer in the second option. Four experimental blocks were generated based on a full factorial design, with a set of filtering rules applied to exclude implausible scenarios. All attribute definitions and corresponding levels are presented in Table 1, whereas the mode combinations featured across the four blocks are summarized in Table 2, along with the collected stated preferences for each scenario.

Invitations were sent through four channels:

- *Donkey Republic* (DR)—bike-sharing service, approximately 6 000;
- *Mobility*—car-sharing service, approximately 1 000;
- Modus Foundation's panel—approximately 1 700;
- TPG's panel—Geneva's main public transport operator, approximately 8 000, mainly to individuals with public transportation subscriptions.

Table 1: Description and possible levels of attributes considered in the survey.

Alternative	Attribute	Description	Levels
Direct	mode_0	Mode: 1—tram, 2—bus	$\{1, 2\}$
	tveh_0	In-vehicle time [min]	$\{30, 35\}$
Transfer	mode_{1A}	First mode: 1—tram, 2—bus, 3—bike, 4—shared bike	$\{1, 2, 3, 4\}$
	mode_{1B}	Last mode: 1—tram, 2—bus, 3—bike, 4—shared bike	$\{1, 2, 3, 4\}$
	tveh_{1A}	In-vehicle time, first mode [min]	$\{5, 10, 15\}$
	tveh_{1B}	In-vehicle time, last mode [min]	$\{5, 10\}$
	twalk	Walking time [min]	$\{0, 2, 4, 6\}$
	twait	Waiting time [min]	$\{0, 2, 5, 8\}$

Table 2: Mode combinations and collected stated preferences per scenario.

Block	Scenario			Collected stated preferences	
	mode_0	mode_{1A}	mode_{1B}	Direct	Transfer
1	tram	tram	shared bike	514 (80.4%)	125 (19.6%)
	tram	tram	bus	451 (70.6%)	188 (29.4%)
	bus	bike	tram	324 (50.7%)	315 (49.3%)
2	bus	bus	shared bike	564 (84.4%)	104 (15.6%)
	bus	bike	tram	487 (72.9%)	181 (27.1%)
	bus	bus	shared bike	416 (62.3%)	252 (37.7%)
3	tram	tram	shared bike	503 (80.2%)	124 (19.8%)
	tram	bike	tram	496 (79.1%)	131 (20.9%)
	bus	tram	shared bike	400 (63.8%)	227 (36.2%)
4	bus	shared bike	tram	530 (83.1%)	108 (16.9%)
	bus	bus	bike	497 (77.9%)	141 (22.1%)
	bus	bike	tram	418 (65.5%)	220 (34.5%)
Sample total				5 507 (71.3%)	2 212 (28.7%)

Overall, 2 572 surveys were completed, corresponding to a participation rate of 15.4% and yielding a total of 7 716 choice observations. Table 3 presents some characteristics of the resulting sample and a comparison with official statistics and recent censuses. Our sample skews older than the general population, with a mean age of 46 compared to the official average of 41. This difference is mainly due to the exclusion of individuals under 15 years old, although respondents over 65 are also underrepresented. The sample further exhibits a significantly higher proportion of male participants than in the general population, and part-time workers are overrepresented at the expense of full-time workers and retirees.

Table 3: Characteristics of the sample and comparison with official statistics and recent censuses. The official statistics are obtained from the Cantonal Statistical Office (OCSTAT) and refer to 2024. The latest censuses available are the 2023 Structural Survey (SS) from the Federal Statistical Office and the 2021 Mobility and Transport Microcensus (MTMC) from the Federal Office for Spatial Development.

	This sample		OCSTAT (2024)	SS (2023)	MTMC (2021)
Age:					
0–14	0	0.0%	15.3%		
15–24	257	10.0%	11.5%		
25–34	480	18.7%	14.3%		
35–44	493	19.2%	15.0%		
45–54	556	21.6%	14.5%		
55–64	407	15.8%	12.7%		
65–74	253	9.8%	7.8%		
75–84	117	4.6%	6.1%		
85+	9	0.3%	2.8%		
Gender:					
male	1 440	56.0%	48.4%		
female	1 132	44.0%	51.6%		
Employment status:					
student	271	10.5%		9.4%	
part time	1 157	44.9%		16.4%	
full time	587	22.9%		37.5%	
not employed	414	16.1%		16.9%	
retired/pensioner	143	5.6%		19.8%	
Bike ownership:					
yes	1 056	56.1%			53.5%
no	1 516	43.9%			46.5%
DR account:					
yes	492	19.1%			
no	2 080	80.9%			

Prior to estimating any model, approximately 10% of the surveys are set aside for out-of-sample validation, yielding an estimation sample of 2 315 individuals—*i.e.*, 6 945 choice observations—and a validation sample of 257 individuals—*i.e.*, 771 choice observations.

3 Modeling approach and results

To estimate the PTPs associated with different mode combinations, we develop a series of binary logit models using the stated-preference data collected through the survey. We begin by applying the assisted specification algorithm proposed by Ortelli *et al.* (2021) to identify relevant variables and interaction effects; the resulting specifications then serve as a basis for further manual refinement, aimed at ensuring consistency with behavioral expectations. Notably, although each respondent completed three scenarios—introducing potential correlation across observations—random agent effects are not included during the automated modeling phase, as doing so would render the computation intractable. Instead, these effects are incorporated later, during the manual modeling stage.

3.1 Assisted specification algorithm

The algorithm developed by Ortelli *et al.* (2021) relies on user-defined "catalogs" of potential explanatory variables, interactions, and non-linear transformations, to automatically generate and evaluate candidate models. Starting from an initial specification, the algorithm iteratively tests incremental modifications to the utility functions while relying on a multi-objective metaheuristic to guide the exploration of the search space. The output is a set of Pareto-optimal model specifications that offer optimal trade-offs between the selected objectives: in this case, we aim at identifying models that maximize the model fit—in terms of log-likelihood—while minimizing the number of estimated parameters.

We define the following catalogs, yielding nearly 50 000 distinct model specifications:

Travel time In-vehicle time (IVT) is associated with mode-specific parameters for both alternatives, with the possibility to assign a common parameter for tram and bus, as well as for bike and shared bike. We also consider two optional interactions: (i) an adjustment term for shared-bike travel time applicable to Donkey Republic (DR) users; and (ii) a similar adjustment for conventional bike travel time for respondents who report owning a bicycle. Walking and waiting times are included by default.

Pure transfer penalty The PTPs are captured by six mode-pair-specific constants included in the utility function of the *transfer* alternative: (i) *tram–bus*; (ii) *tram–shared bike*; (iii) *bus–bike*; (iv) *bus–shared bike*; (v) *bike–tram*; and (vi) *shared bike–tram.*

Gender The effect of gender is either (i) captured by a single parameter, (ii) included as an interaction with the PTP constants, or (iii) disregarded.

DR account In addition to a possibly lower sensitivity to shared-bike travel time, we assume that users—including those with pay-as-you-go membership plans—may also perceive lower inconvenience from transfers involving shared bikes, reflecting differences in familiarity or ease of access.

Bike ownership Similarly, we also assume that bike ownership—including e-bikes—may influence the perceived inconvenience of transfers that involve a personal bike.

Employment status Respondents' employment status is considered through three alternative dummy variables: (i) student, (ii) retired, and (iii) nonworker, *i.e.*, the two combined. Only one of these dummy variables may be included, or none.

Age The effect of age is assumed to vary depending on whether or not the *transfer* alternative includes an active mode—*i.e.*, bike or shared bike. A linear specification is assumed, with the effect beginning at a threshold age. The algorithm is provided with a discrete set of candidate thresholds ranging from 20 to 75.

The assisted specification algorithm is run using the implementation available in the *Biogeme* package for Python (Bierlaire, 2023),[1] with 500 search attempts. In each attempt, a solution is drawn from the current Pareto set and incrementally modified with the goal of improving its performance. Up to 20 neighboring specifications are evaluated per attempt, each generated by introducing small changes to the selected solution. In line with economic theory, we impose all parameters related to time and PTPs to be negative; any specification that yields a positive estimate for any of them is deemed invalid.

In total, 1 354 distinct specifications are generated and tested by the algorithm, with 111 discarded for violating the sign constraints. The final Pareto set is made up of 8 models, ranging from 10 to 20 parameters and from −0.561 to −0.530 in terms of log-likelihood achieved on the estimation data.[2,3] On the validation sample, log-likelihoods range from −0.585 to −0.533, with the best fit achieved by the 15-parameter specification. The performance and estimates of the Pareto-optimal models are compared in Table 4.

[1] A comprehensive description of the implementation is available in (Bierlaire and Ortelli, 2023).
[2] All log-likelihoods are normalized by the number of observations in their respective samples.
[3] For the sake of comparison, the null log-likelihood of all models is equal to −0.693.

Overall, the obtained parameter estimates are realistic and display stability across the eight models in the Pareto set. Travel-time sensitivity parameters present a behaviorally consistent order: tram/bus serves as the baseline, followed by bike/shared-bike, then walking, and finally waiting time, which is perceived almost twice as negatively as the baseline. None of the specifications distinguish between tram and bus, nor between bike and shared bike, in terms of travel-time sensitivity. Similarly, although the catalogs allowed for interaction terms to reflect potentially lower disutility among DR users and bike owners, such adjustments were not selected in any model. Given the intuitive appeal of these effects, their absence likely reflects limitations in the search coverage of the algorithm rather than an indication that these factors are behaviorally irrelevant.

The estimated PTPs are broadly consistent with the values found in the existing literature.[4] Transfers involving shared bikes are assigned the highest disutility—particularly when shared bike is the second mode, possibly reflecting uncertainty associated with availability at the transfer station and the inconvenience this could create midway through a trip. Still, models that include the DR account dummy variable show that DR users perceive significantly lower disutility for those same transfers. In fact, for them, shared-bike-related penalties are even lower than those involving conventional bikes, suggesting that familiarity makes docking a shared bike more convenient than managing a personal one during a transfer. The lowest PTPs—*i.e.*, the smallest inconvenience—are associated with *tram–bus* transfers, followed closely by *bus–bike*—particularly among bike owners.

Effects of socioeconomic characteristics are captured through both main effects and interaction terms. Gender is modeled either via a single parameter—in the 12- to 16-parameter models—or through gender-specific transfer penalties—in the 20-parameter model. Across both formulations, results show that men perceive transfers less negatively than women, in most cases by several EIVMs. As regards age, the algorithm introduces additional penalties for transfers involving active modes starting as early as age 20—approximately one extra EIVM every 5 to 7 years of age—suggesting that even young adults perceive such combinations as burdensome or undesirable. Conversely, a second age-related effect shows that transfers that do *not* involve active modes are progressively less inconvenient as age increases—about one fewer EIVM every 12 to 13 years—relative to the direct alternative. This latter effect lacks a clear behavioral explanation and may be due to spurious correlations in the data. Finally, employment-related effect retained by the algorithm is the one associated with nonworkers, which appears only in the 16-parameter specification. Its estimated parameter is statistically nonsignificant—t-stat = 0.358—indicating limited explanatory power within the current modeling framework.

[4] See (Yap *et al.*, 2024) for a comparison across studies.

Table 4: Performance and parameter estimates of the algorithm-generated models. The estimation and validation log-likelihoods (LL) are normalized by the respective sample sizes. All parameter estimates are reported in equivalent in-vehicle minutes (EIVM). Values in parentheses present a t-stat lower than 1.96 in absolute value.

Model performance								
Number of parameters	10	11	12	13	14	15	16	20
Norm. LL, estimation	−0.561	−0.547	−0.541	−0.533	−0.532	−0.531	−0.531	−0.530
Norm. LL, validation	−0.585	−0.562	−0.564	−0.536	−0.536	−0.533	−0.534	−0.535
Parameter estimates [EIVM]								
IVT, tram/bus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IVT, bike/shared bike	1.23	1.25	1.21	1.24	1.22	1.25	1.26	1.23
Walking time	1.57	1.66	1.53	1.64	1.61	1.65	1.66	1.62
Waiting time	1.86	1.88	1.83	1.88	1.88	1.91	1.92	1.88
PTP tram–bus	5.49	4.91	7.26	6.49	6.26	8.19	8.32	
female								7.69
male								5.61
PTP tram–shared bike	13.97	15.36	11.51	13.75	12.93	13.61	13.92	
female								13.74
male								10.75
PTP bus–bike	8.75	7.97	6.64	7.01	7.48	7.99	8.18	
female								8.50
male								(4.87)
PTP bus–shared bike	12.50	14.06	10.07	12.43	11.63	12.22	12.52	
female								13.40
male								8.37
PTP bike–tram	9.56	8.99	7.33	7.92	8.44	8.96	9.23	
female								9.52
male								5.79
PTP shared bike–tram	10.22	11.67	7.88	10.21	9.25	9.93	10.28	
female								8.84
male								8.10
Male			−3.97	−3.65	−3.39	−3.47	−3.52	
DR account		−10.72		−7.78	−7.76	−7.85	−7.90	−7.76
Bike ownership					−2.78	−2.79	−2.77	−2.67
Nonworker							(−0.16)	
Age, active mode								
starting at 20			0.17		0.14			
starting at 30				0.17		0.16		
starting at 35							0.18	0.18
Age, no active mode								
starting at 20						−0.08	−0.08	−0.08

3.2 Manual specification with random agent effect

Building on the results of the assisted specification algorithm, we implement a series of manual refinements to better capture unobserved heterogeneity and enhance plausibility. The most notable modification is the inclusion of random agent effects to account for correlation across the three choice scenarios completed by each respondent. The random terms—one per alternative—are assumed to be normally distributed, and their scales are estimated with the other model parameters via maximum simulated likelihood. After a series of trial-and-error iterations, our final model includes 17 parameters and achieves a log-likelihood of -0.464 and -0.474 on the estimation and validation datasets, respectively. The obtained parameter estimates are presented in Table 5.

While slightly inflated, the estimated values for the travel-time components are in line with those observed in the algorithm-generated models, with the key difference that we now include an adjustment term for respondents who hold a DR account. These individuals exhibit a lower sensitivity to shared-bike IVT—by 0.31 EIVM—compared to non-users, suggesting that sensitivity to travel time depends on the level of familiarity of individuals with the bike sharing system. However, one should note that the resulting disutility among DR users is even lower than the one associated with tram/bus IVT, which may be associated with some form of choice-supportive bias.

The structure of transfer penalties is largely consistent with previous models; however, the magnitude of the penalties in the manually specified model is generally lower, which may be attributed to the random agent effects absorbing part of the unobserved heterogeneity previously captured by inflated PTP estimates. Notably, the value of 3.54 EIVM associated with the *tram–bus* pair is particularly low compared to the existing literature: only Yap *et al.* (2024) report a similar estimate—3.59 EIVM—for cross-platform metro transfers in London, which presumably offer a higher degree of physical and operational integration than a typical tram-to-bus transfer in Geneva. Moreover, several PTP estimates also exhibit wide bootstrapped confidence intervals—*e.g.*, $[0.22, 6.60]$ for *tram–bus*—reflecting statistical uncertainty likely linked to limitations inherent to stated-preference data.

As for socioeconomic characteristics, the effect of gender is now limited to transfers involving active modes, where male respondents exhibit significantly lower disutility. Effects associated with DR account and bike ownership are also retained, reinforcing the role of familiarity in reducing transfer aversion. The age-related penalty for active-mode transfers—applied from age 30 onward—remains modest but statistically significant, and employment status is excluded from the final model due to limited explanatory power.

Finally, the estimated scale parameters of the random agent effects are large, indicating substantial unobserved heterogeneity in individual preferences and confirming that perceived transfer disutility varies considerably across respondents. However, the magnitude of these estimates may also suggest that relevant explanatory variables remain insufficiently captured in the current specification. Further research incorporating richer data could help better account for this heterogeneity and improve model interpretability.

Table 5: Parameter estimates of the manually specified model. Confidence intervals (CIs) are computed via bootstrapping with 100 resamples.

	Value	Rob. t-stat	EIVM	[90% CI]
IVT tram/bus	−0.249	−9.22	1.00	[1.00, 1.00]
IVT bike/shared bike	−0.338	−15.2	1.36	[1.14, 1.68]
IVT shared bike adjust., DR users	0.103	3.37	−0.41	[−0.71, −0.18]
Walking time	−0.444	−12.6	1.78	[1.50, 2.24]
Waiting time	−0.494	−14.0	1.98	[1.73, 2.36]
PTP tram–bus	−0.882	−1.73	3.54	[0.22, 6.60]
PTP tram–shared bike	−3.14	−5.35	12.64	[10.07, 14.41]
PTP bus–bike	−1.67	−2.19	6.70	[2.00, 10.46]
PTP bus–shared bike	−2.89	−4.48	11.60	[8.44, 13.63]
PTP bike–tram	−1.87	−2.86	7.50	[3.80, 9.99]
PTP shared bike–tram	−2.42	−3.99	9.71	[6.25, 11.86]
Male, active mode	0.896	5.91	−3.60	[−5.46, −2.62]
DR subscription	0.683	2.49	−2.74	[−4.74, −1.37]
Bike ownership	0.430	2.89	−1.73	[−3.15, −0.87]
Age, active mode, starting at 30	−0.0425	−8.77	0.17	[0.14, 0.22]
Agent effect scale, direct alternative	1.37	9.22	5.50	[1.62, 8.75]
Agent effect scale, transfer alternative	2.17	16.8	8.70	[5.95, 11.53]

4 Conclusion

This study represents an initial effort to better understand how transfer penalties vary across different mode combinations in the context of intermodal travel involving shared mobility services. Using stated-preference data collected in Geneva in 2024, we estimate mode-pair-specific pure transfer penalties (PTPs) through a series of binary logit models. Our modeling approach combines an assisted specification algorithm with manual refinements to ensure behavioral plausibility and to account for correlation across multiple observations from each respondent.

Results confirm that transfer disutility is highly context-dependent: transfers involving shared bikes are perceived as the most burdensome—particularly when the shared bike is used in the second leg of the trip—but familiarity with the bike sharing system is identified as a key moderating factor: indeed, *Donkey Republic* subscribers exhibit a notably lower disutility for transfer involving shared bikes compared to non-subscribers as well as for shared-bike IVT, suggesting that habitual use or confidence in the service reduces perceived inconvenience. To a lesser extent, bike owners also benefit from a reduction in perceived disutility for transfers involving personal bikes, and socio-demographic factors such as age and gender further contribute to explaining heterogeneity in transfer perceptions. Finally, the inclusion of agent-specific random effects captures substantial residual variation across individuals and contributes to improved model fit.

While the results presented in this study are encouraging, the analysis also highlights several limitations and directions for future research. First, our findings are based on data from the first of two surveys and should therefore be considered exploratory. One of the primary objectives of this initial phase is to inform the design of the second survey, which will incorporate a wider range of transfer combinations—particularly those involving active modes and shared micromobility—to expand the scope of this analysis. Second, although stated-preference data are well suited for capturing hypothetical and emerging travel behaviors, they can lack realism and introduce a variety of biases in the participants' responses. This is reflected in the wide confidence intervals associated with some PTP estimates. To address this limitation, future work should also integrate revealed-preference data and consider hybrid modeling approaches that leverage the strengths of both data types. Lastly, the collection of more detailed information on respondents' characteristics, travel habits, attitudes, and constraints would help better account for the substantial unobserved heterogeneity identified in the current models.

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