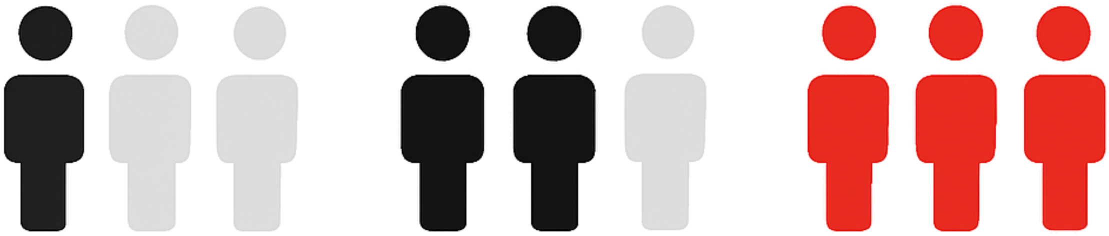

Stated preference survey 2025 on mode, route and departure time choices

Response behavior, data quality checks and preliminary results

Basil Schmid

Mathilde Ruyssen, Sylvie Gayda, Nicolas Moreau, Pauline Quittelier

Marco Kouwenhoven, Jeroen Muller, Rodrigo Tapia

Michel Bierlaire

STRC Conference Paper 2026 **April 17, 2026**

STRC | **26th Swiss Transport Research Conference**
Monte Verità / Ascona, May 20-22, 2026

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Basil Schmid
Federal Office for Spatial Development ARE
basil.schmid@are.admin.ch

Mathilde Ruyssen, Sylvie Gayda, Nicolas Moreau, Pauline Quittelier
STRATEC

Marco Kouwenhoven, Jeroen Muller, Rodrigo Tapia
Significance

Michel Bierlaire
EPFL

April 17, 2026

Abstract

This paper documents the main outcomes of the Swiss stated preference (SP) survey 2025 and provides a first assessment of data quality and the plausibility of preliminary RP/SP choice models. The SP survey is linked to the Swiss Mobility and Transport Microcensus (MTMC) and uses pivoted choice tasks based on respondents' observed trips, including individualized and behaviorally realistic choice situations. Compared to previous MTMC-linked SP surveys, the 2025 design includes several methodological improvements, notably a more realistic treatment of travel costs, a simplified and more consistent questionnaire layout and a refined assignment of SP experiments.

The final raw dataset comprises 93'935 choice observations from 7'757 RP respondents, of whom 6'182 completed the SP survey – the largest dataset in the history of MTMC-linked SP surveys. Response rates are satisfactory, with a total net response rate of 49.3% and a response rate conditional on successful recruitment of 80.6%. A major remaining data quality issue is related to non-trading behavior, particularly in SP1 mode choice, where strong modal preferences appear to play an important role. In SP2 and SP3, non-trading is less frequent but somewhat higher than in previous SP surveys, likely reflecting narrower and more realistic attribute ranges. Overall, the preliminary RP/SP models yield stable, significant and behaviorally plausible parameter estimates, indicating that the 2025 survey provides a strong empirical basis for subsequent model development and policy-oriented analysis. Compared to previous MTMC-linked SP surveys, the trends in attribute sensitivities point towards an increased value of travel time (VTT).

Keywords

Stated preferences; survey design; mode choice; route choice; departure time choice; pooled RP/SP choice models; heterogeneity in trip distance and purpose

Preferred citation

Schmid, B., M. Ruyssen, S. Gayda, N. Moreau, P. Quittelier, M. Kouwenhoven, J. Muller, R. Tapia and M. Bierlaire (2026) SP survey 2025 on mode, route and departure time choices, paper presented at the *26th Swiss Transport Research Conference (STRC 2026)*, Ascona, May 2026.

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1 Introduction

The stated preference (SP) survey on travel choices has been conducted since 2010 under the lead of the Swiss Federal Office for Spatial Development (ARE). It is directly linked to the revealed preference (RP) survey *Swiss Mobility and Transport Microcensus* (MTMC), carried out by the Swiss Federal Statistical Office (FSO) in collaboration with the ARE. The main purpose of the SP survey is to estimate sensitivities and preferences with respect to key transport-related level-of-service (LOS) attributes, such as travel time and travel cost, by combining observed and hypothetical choice situations. The results are an important basis for the Swiss national transport model (ARE, 2026), the Swiss transport perspectives (ARE, 2022b) as well as Swiss cost-benefit analyses.

Respondents are asked to choose between alternative transport modes, routes and departure times, with the SP tasks pivoted around their actual travel behavior observed in the MTMC (all details, see in Schmid *et al.*, 2025). The survey covers the Swiss resident population aged 18 and older who were mobile on the MTMC reference day. It is conducted after the CATI-based MTMC interview using either online (CAWI) or paper (PAPI) questionnaires, with a sample size in 2025 of more than 6'000 respondents (around 10% of the MTMC sample). Participation is voluntary. Previous MTMC-linked SP surveys were conducted in 2010, 2015 and 2021 (see also ARE, 2012, 2016, 2022a). The SP responses are merged with the MTMC data, making rich sociodemographic information available for analysis.

This paper documents the outcomes of the SP survey 2025 and provides a first assessment of the data quality, behavioral plausibility and modeling potential of the resulting RP/SP dataset. Its primary aim is to evaluate the quality of the collected SP data and to assess whether the preliminary estimation results are sufficiently robust and plausible to serve as a solid basis for the subsequent modeling efforts.

The paper first summarizes the main design principles of the 2025 survey and highlights the most important methodological improvements compared to previous SP surveys, including the revised construction of pivoted SP tasks, the more realistic treatment of travel costs and the refined questionnaire layout (Section 2). The response rates are documented in Section 3, distinguishing between the pre-test and main survey waves. Section 4 then documents the sample characteristics and the main quality indicators of the collected data, including response times, completion/non-response patterns and the distribution of the main characteristics of the RP reference trips. Particular attention is given to non-trading behavior and related response patterns, as they constitute a main data quality challenge in the current SP survey. Finally, Section 5 reports preliminary choice models estimated separately for each data/experiment type as well as for a pooled RP/SP model. These models are primarily intended as a consistency and plausibility check: They allow us to verify whether the main behavioral trade-offs are identified in the expected direction and order of magnitude and whether the revised survey design has succeeded in producing data that are suitable for more advanced model development. Section 6 discusses the main findings and presents the conclusions.

2 SP survey 2025: Survey concept and overall structure

This section provides a overview of the main design principles and methodological innovations of the SP survey 2025, as discussed in detail in Schmid *et al.* (2025). The current survey builds on the SP survey 2021 and retains its four core SP experiments, while introducing a number of improvements aimed at increasing behavioral realism, improving comparability with national modeling applications, reducing respondents' cognitive burden and strengthening the informational content of the resulting data.

As in 2021, the SP survey 2025 consists of four stated preference experiments: **SP1** on mode choice, **SP2** on car route choice, **SP3** on public transport (PT) route choice and **SP4** on departure time choice. A central design principle is the use of an individualized *reference trip* from the MTMC as the basis for the SP questions. This pivoting approach ensures that the survey remains tailored to each respondent.

Comparability with the 2021 survey was preserved wherever possible. Nevertheless, several targeted revisions were introduced, including simplified choice tasks, revised layouts, improved attribute definitions and a redesigned SP4 experiment. In particular, SP4 no longer combines mode and departure time choice, but focuses exclusively on departure time choice, thereby reducing complexity for respondents.

2.1 Dynamic pricing and more realistic travel cost calculation

Similarly to the SP survey 2021, a dynamic pricing concept is explicitly incorporated. Temporal differentiation is directly implemented in the survey via a *peak charge*, which is added separately to travel costs when a trip takes place during peak hours and in a congested area. Peak periods are defined as 7–9 AM and 4–6 PM on weekdays. The same general logic is applied to both car and PT in order to remain consistency between the two modes.

By contrast, spatial differentiation is not explicitly represented in the SP attributes. Instead, it is introduced conceptually in the survey instructions, where congestion is defined on the basis of the origin and/or destination being located in an urban or intermediate area. This solution avoids excessive respondent burden while still allowing future policy scenarios with spatial differentiation to be tested later, e.g. in the national passenger transport model.

Another major improvement concerns the calculation of RP travel costs. For car trips, the survey no longer relies on a simple average cost factor by trip distance. Instead, vehicle-specific information from the MTMC is linked with the IVZ vehicle database and TCS data on variable costs. A regression-based prediction model is used to derive individualized variable car cost factors as a function of key vehicle attributes such as engine power, weight and fuel type. These predicted variable costs are then applied to routed trip distances using a degressive cost function, which helps to increase realism and weaken the correlation between time and cost.

For PT, the 2025 survey adopts a similarly behaviorally grounded approach. In contrast to previous surveys, only *variable* PT costs are considered relevant in short-term choices. This implies, for example, that holders of a *GA* face zero PT costs at the trip level. For other subscription types, travel costs are derived using a set of assumptions based on trip purpose, distance, home-based versus non-home-based trips and the SBB tariff structure. These refinements substantially increase the realism of the PT cost attributes.

2.2 Main improvements in the SP experiments and layout

Beyond the cost calculation, the 2025 survey introduces a number of important improvements to the SP experiments themselves. First, several attributes from the 2021 survey were removed, most notably the risk and duration of delay, because they were often misunderstood and could not be robustly estimated. At the same time, new or refined attributes were introduced where they were considered behaviorally more meaningful. In SP1, for example, access/egress time was added for both (E-)Bike and car, improving consistency with PT and increasing realism.

Second, the presentation of the SP tasks was substantially revised. The total travel time and total travel cost are no longer shown in the SP1–SP3 choice tasks, because pre-test feedback suggested that respondents tended to focus only on these totals rather than on the separate attributes. Instead, the 2025 survey uses a cleaner table-based layout, where all relevant attributes are presented in a single matrix with empty cells for non-applicable alternatives. The visualization of PT crowding was also improved by replacing drawn descriptions with the official SBB-layout (see Fig. 1).

Figure 1: Level of crowding (low/medium, high and very high) according to the Swiss Federal Railways (SBB).

Third, the set of available alternatives is now tailored more carefully to each respondent. In SP1, the (E-)Bike alternative is only shown if the respondent actually has access to an (E-)Bike and the trip distance falls below an (E-)Bike-type-specific threshold. Moreover, trips without a PT alternative are no longer automatically excluded from the survey, which broadens the coverage relative to 2021.

2.3 Questionnaire logic and experimental design

The assignment of SP experiments was also made more flexible. The SP survey 2025 distinguishes 41 types, based on the respondent's current mode, car availability, PT availability, trip distance, (E-)Bike availability and whether peak-hour conditions are met. This more detailed logic allows the questionnaire to be tailored more closely to the respondent's actual situation.

The structure of the individual experiments was also refined. SP2 and SP3 continue to focus on route choice, but the attribute sets are now more aligned with the corresponding SP1 mode choice attributes. SP4 was completely redesigned as a pure departure time experiment with five alternatives per choice task, constructed such that none of the alternatives is clearly dominant. This strengthens behavioral realism while reducing task complexity.

The factorial designs were improved as well. Compared to 2021, the number of design blocks increased from two to eight, while each respondent still only answers one randomly assigned block of six tasks. In addition, a new 60+ km distance class was introduced and travel time and cost attributes now include a fifth level corresponding to a 0% change relative to the respondent's reference trip. This increases design realism and improves the variation in observed trade-offs. As in 2021, the designs were generated in *Ngene* (ChoiceMetrics, 2025) using a D-efficient approach with priors based on re-estimated 2021 models.

2.4 Additional qualitative information

Finally, the 2025 survey includes a new qualitative question on the reasons for choosing the RP mode. This question is asked once after SP1 and asks respondents to rate the importance of various decision criteria, including travel time, travel cost, convenience, flexibility, weather, comfort, health, environmental impact and trip chaining. The purpose of this addition is to complement the measurable level-of-service (LOS) attributes with factors that are often behaviorally important but difficult to observe directly. This extension is expected to enrich the later analysis by allowing the role of attitudes, habits and contextual influences to be studied more explicitly in combination with the SP responses.

3 Response behavior

The recruitment periods for the pre-test and three main waves were as follows: The **pre-test** ran from March 24 until May 27 2025, the **first main wave** from June 16 to July 20 2025, the **second main wave** from September 1 to October 5 2025, and the **third main wave** from October 27 to November 30 2025.

Table 1 shows the response behavior in the SP survey 2025 for each subwave. Across the pre-test and all three main waves, a total of 9'368 MTMC respondents were successfully recruited to participate in the SP survey and questionnaires were prepared and sent to 7'731 of them. The difference between the number of respondents *recruited* and those actually *receiving* a questionnaire is mainly due to the various selection and exclusion criteria applied during questionnaire generation. In total, 6'235 respondents returned the SP questionnaire, corresponding to a very satisfactory response rate of 80.6% among those who had committed to participate (R2; calculations according to Schmid and Axhausen (2019)). The resulting total net response rate (R1) is 49.3%. In other words, more than four out of five MTMC respondents who had agreed to participate ultimately completed the SP survey, while a substantial share of eligible MTMC respondents did not agree to participate in the first place. After preliminary quality checks and the exclusion of invalid questionnaires, 6'182 questionnaires were retained as valid responses.

Table 1: Response behavior in the pre-test and main survey waves.

Description	**Pre-test**	**Wave 1**	**Wave 2**	**Wave 3**	**Total**
Eligible respondents (#)	3'393	3'627	4'507	3'785	15'312
Eligible respondents (%)	100.0%	100.0%	100.0%	100.0%	100.0%
Recruited respondents (#)	2'199	2'291	2'679	2'199	9'368
Recruited respondents (%)	64.8%	63.2%	59.4%	58.1%	61.2%
SP questionnaires sent (#)	1'826	1'896	2'153	1'856	7'731
SP questionnaires sent (%)	100.0%	100.0%	100.0%	100.0%	100.0%
SP questionnaires received (#)	1'437	1'537	1'762	1'499	6'235
Response rate of the committed (R2; %)	78.7%	81.1%	81.8%	80.8%	80.6%
Response rate total (R1; %)	51.0%	51.2%	48.7%	46.9%	49.3%
CAWI (#)	1'103	1'148	1'344	1'165	4'760
CAWI (%)	73.3%	72.2%	76.2%	77.7%	76.3%
PAPI (#)	334	389	418	334	1'475
PAPI (%)	26.7%	27.8%	23.8%	22.3%	23.7%
Invalid SP questionnaires (#)	22	6	21	4	53
Total SP questionnaires (#)	1'415	1'531	1'741	1'495	**6'182**

4 Data and quality checks

4.1 Sample characteristics

The initial raw dataset (i.e., before the exclusion of *non-plausible* responses) consists of 6'182 SP-respondents, the largest sample size in the history of SP-surveys linked to the MTMC (ARE, 2012, 2016, 2022a).

Pooling RP and SP observations yields a raw dataset with **93'935 choice situations** from **7'757 RP respondents**, of whom **6'182** completed the SP survey. The RP part includes routed MTMC trips for all 7'757 respondents, including some respondents who received but did not complete the SP questionnaire.

Table 2 summarizes the main characteristics of the dataset. On the observation level, 37.6% of all observations are SP1 mode choice tasks, 25.7% RP mode choice tasks, 21.4% SP2 car route choice tasks, 10.4% SP3 PT route choice tasks and 5.0% SP4 departure time tasks. Compared to earlier SP surveys, the RP component is substantially larger, because – whenever possible – multiple RP trips per respondent were routed and retained.

The sample is well balanced across pre-test and main waves, which is useful for later analyses of possible seasonal effects. The language distribution is broadly consistent with the Swiss population. The large majority of respondents completed the survey online (76.6% CAWI), while 23.4% used the paper questionnaire (PAPI), implying a noticeable reduction in PAPI participation compared with 2021.

Regarding the ownership of mobility tools, 87.6% of respondents had a car available for at least one RP trip and 71.6% held some form of PT season ticket relevant for trip-level variable cost calculation. Regarding bike availability in SP1, 16.0% had no bike available, 32.3% had a regular bike, 36.0% a slow E-bike and 15.6% a fast E-bike available. Overall, the SP sample appears highly mobile, particularly with respect to PT subscriptions and bike availability (see e.g. discussions in Schmid, 2019). A more detailed assessment of representativeness and response bias will be part of the follow-up project using MTMC weights and sociodemographic variables.

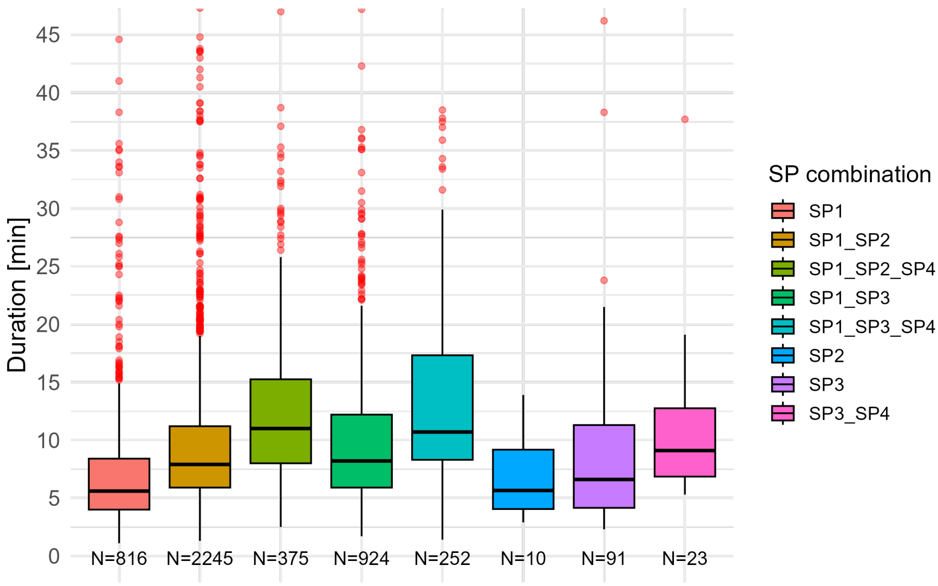
Table 2: Characteristics of the raw dataset (7'757 RP respondents; 6'182 SP respondents; 93'935 choice observations).

Characteristic	**Category**	**Share [%]**
Data type (choice observation level)	RP mode choice	25.7
	SP1 mode choice	37.6
	SP2 route choice car	21.4
	SP3 route choice PT	10.4
	SP4 departure time choice	5.0
Wave (respondent level)	Pre-test (Spring 2025)	22.9
	Wave 1 (Summer 2025)	24.8
	Wave 2 (Autumn 2025)	28.2
	Wave 3 (Winter 2025)	24.2
Language (respondent level)	CH-German	66.6
	CH-French	29.1
	CH-Italian	4.3
Questionnaire (respondent level)	Online (CAWI)	76.6
	Paper (PAPI)	23.4
Gadget type (respondent level; CAWI only)	Mobile phone	30.9
	PC, Laptop, Tablet	69.1
Car available in any RP trip (respondent level)	No	12.4
	Yes	87.6
Any type of PT season ticket (respondent level)	No	28.4
	Yes	71.6
Available bike type in SP1 (respondent level)	No (E-)Bike available	16.0
	Regular bike available	32.3
	Slow E-bike available	36.0
	Fast E-bike available	15.6

4.2 Response time (CAWI)

Response times in the full CAWI dataset are very similar to those in the pre-test. The average completion time is about 10 minutes (capped at 90 minutes), while the median is 7.9 minutes. As shown in Fig. 2, response times vary by questionnaire type and less than about two minutes per SP type appears unrealistically low once instructions and attribute descriptions are taken into account.

Figure 2: Response time distribution CAWI (N = 4'736), by SP combination.



4.3 Completed choice tasks (PAPI)

The PAPI data also indicate good survey completion quality. As shown in Table 3, only a small number of respondents completed fewer than five choice tasks, mainly in SP1 and SP2. In most cases, all six tasks were completed. This suggests that dropout within the paper questionnaire was limited and did not constitute a major operational issue.

Table 3: Completed choice tasks PAPI (N = 1'446) in the raw dataset.

	Completed choice tasks						
SP type	**1**	**2**	**3**	**4**	**5**	**6**	**# total**
SP1	66	25	22	23	61	1'179	1'316
SP2	53	5	0	3	12	695	768
SP3	14	4	3	0	9	317	347
SP4	8	4	0	2	3	118	135

4.4 Distribution of RP trip characteristics

The selected RP reference trips again achieve a satisfactory balance in terms of distance, departure time and trip purpose. The expected morning and afternoon peaks are clearly visible and the purpose distribution is similar to that in the MTMC 2021 (FSO/ARE, 2023). Work, shopping and leisure account together for 83.4% of all reference trips. Shopping trips are shortest on average, whereas work and business trips tend to be longer, reproducing the same qualitative pattern as in previous SP surveys.

Figure 3: RP reference trip length distributions if mode is available (left; black box = quantiles; dot = mean) and departure time distributions (right; N = 6'182 respondents).

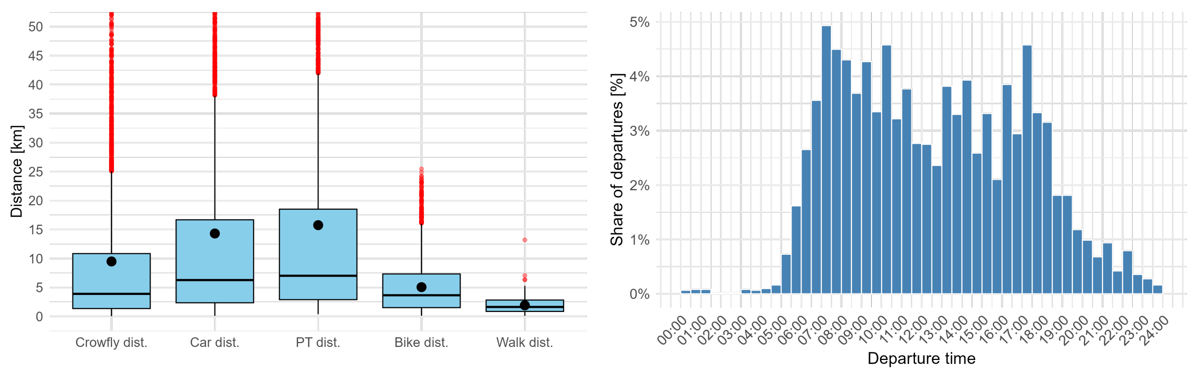
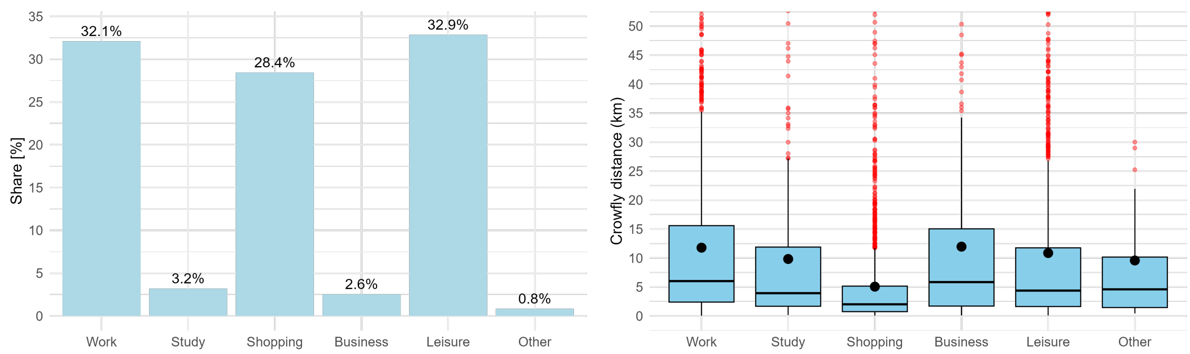


Figure 4: RP reference trip purpose distributions and crowfly distance by purpose (N = 6'182 respondents).



Some distributions changed in the main survey waves relative to the pre-test. The average road distance of the RP reference trips is 13.8 km, i.e. around 1.6 km lower than in the pre-test. The share of return-home trips was reduced substantially from 50.4% in the pre-test to 26.2% in the final raw dataset, although it remains somewhat higher than in earlier SP surveys. By comparison, the overall share of return-home trips in the current RP dataset is around 39.2%, close to the MTMC 2021 value of about 38%. Furthermore, 28.8% of RP reference trips take place during peak hours and in a congested zone, such that a peak charge is shown in the corresponding SP tasks.

The SP1 cross-tabulation in Table 4 confirms a pattern often seen in SP surveys: Compared with RP, car is chosen less often in SP1, whereas PT and particularly (E-)Bike are chosen more often. This likely reflects the hypothetical nature of SP choices, the tailored and sometimes simplified attribute representation, and the fact that respondents may abstract from aspects of the original RP context that are not explicitly shown in SP1.

Table 4: SP1 choices in the raw dataset, by chosen RP travel mode.

	RP mode					
SP1 mode	**Car**	**PT**	**(E-)Bike**	**Walk**	**# total**	**% total**
Car	**14’134**	957	229	323	15’643	44.3%
PT	2’154	**4’471**	236	452	7’313	20.7%
(E-)Bike	1’829	887	**3’533**	906	7’155	20.2%
Walk	497	455	294	**3’986**	5’232	14.8%
# total	18’614	6’770	4’292	5’667	35’343	100.0%
% total	52.7%	19.2%	12.1%	16.0%	100.0%	

When facing hypothetical choices, a respondent may behave in a socially or environmentally desirable way (e.g., in the case of bike), does not consider all the aspects of the original trip (e.g., mode availabilities, costs or other factors) or may react on attributes that were not present in reality (e.g., the peak charge). However, the current approach is specifically designed to best mimic the real world situation, pivoting SP experiments around truly experienced RP reference trips (see e.g. Hensher, 2010). Finally, we have to trust in respondents’ preferences of actually selecting the alternative that they also would choose in reality, conditional on the presented (sometimes more or less hypothetical) attributes in the SP experiment. Potential hypothetical biases are taken into account by pooling the RP and SP data and controlling for observed and unobserved heterogeneity (e.g., the heterogeneity in error variances across respondents and datasets) in the later modeling stage (see e.g. Fifer *et al.*, 2014; Schmid *et al.*, 2019).

4.5 Choice frequencies in each data/experiment type

Fig. 5 (left) shows that compared with the full RP dataset, SP1 shows relatively more choices of PT and (E-)Bike, and fewer of car and walk. The low share of walk is mainly explained by the deliberate selection of longer reference trips for the SP experiments to increase variation (Schmid *et al.*, 2025).

In SP surveys, one should note that the objective is not to reproduce the respondent and/or RP trip distributions 1:1, but to construct efficient experimental designs that maximize variation and balance across attribute levels, thereby revealing respondents' trade-offs more clearly (Louviere *et al.*, 2000; Rose and Bliemer, 2007; Hensher *et al.*, 2015). Any resulting lack of representativeness can later be addressed in model estimation by incorporating observed trip and respondent characteristics, such as distance or trip purpose, through covariates and interaction terms (Train, 2009).

Figure 5: Relative choice frequencies in RP (N = 7'757) and SP (N = 6'182) datasets.

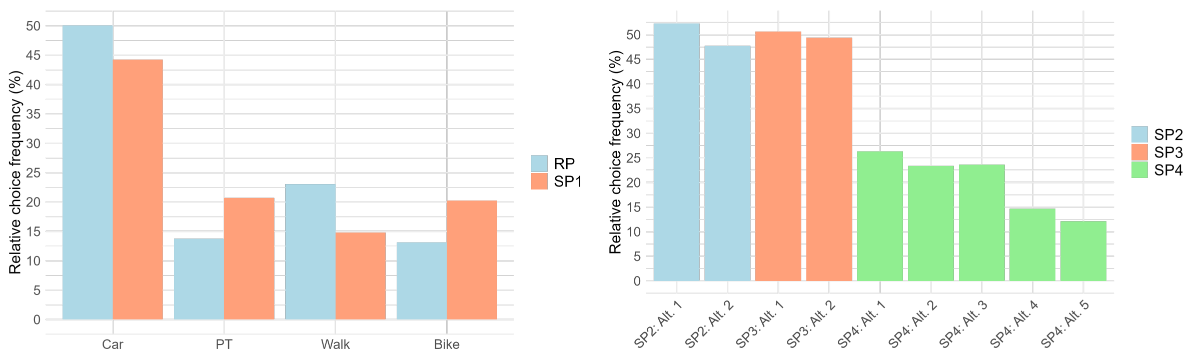


Fig. 5 (right) shows the relative choice frequencies in SP2, SP3, and SP4. For the unlabeled SP2 and SP3 experiments, roughly equal shares between the two alternatives would be expected. SP2 suggests a slight preference for the left alternative, whereas SP3 shows a small preference for the right one. These imbalances are not critical and can be captured by alternative-specific constants (see e.g. Hess *et al.*, 2017). In SP4, earlier departure times are chosen more often, which is plausible because shifting to an earlier departure is more likely, especially for respondents with fixed arrival times.

4.6 Non-trading behavior

Non-trading remains an important issue of the current dataset. Respondents are classified as non-traders if they always choose the same alternative across all choice situations, regardless of the presented attributes. In unlabeled route choice experiments, lexicographic and weak-lexicographic patterns are also considered.

SP1: Mode choice. Among the 5'988 respondents who completed SP1, 4'013 exhibit non-trading behavior, corresponding to 67.0%. This is slightly higher than in previous SP surveys. As shown in Table 5, the largest share of SP1 non-traders repeatedly choose car, followed by (E-)Bike. For a given RP mode, non-trading is especially pronounced among respondents whose RP mode was (E-)Bike or walk. In most cases, respondents stick to their RP mode, which is not inconsistent with rational behavior in a labeled mode choice setting. More critical are those respondents who always choose a *different* mode than in RP; these cases are less frequent but warrant further attention in the later data cleaning and modeling steps.

Table 5: SP1 non-traders (NT) in the raw dataset, by chosen RP travel mode.

	RP mode					
SP1 mode	**Car**	**PT**	**(E-)Bike**	**Walk**	**# total**	**% total**
Car (SP)	**1772**	34	17	21	1844	46.0%
PT (SP)	67	**494**	14	23	598	14.9%
(E-)Bike (SP)	171	79	**524**	115	889	22.2%
Walk (SP)	49	27	37	**568**	681	17.0%
Total NT	2059	634	592	727	4012	–
% NT	65.4%	55.5%	81.3%	74.9%	–	**67.0%**
Full sample	3147	1142	728	971	5988	100%

SP2: Route choice car. Among the 3'398 respondents who completed SP2, 1'064 (31.4%) exhibit non-trading and/or lexicographic behavior. Always choosing the fastest route (12.5%) or the cheapest route (8.7% plus overlap cases) is not necessarily problematic, but the share of respondents always choosing the same alternative regardless of its relative attributes is noticeably larger than in previous SP surveys. This likely relates to the narrower attribute bandwidths in the 2025 design.

Table 6: SP2 (route choice car) non-traders and lexicographic preferences in the raw dataset.

Different alts. chosen?	**Only fastest route?**	**Only cheapest route?**	**# total**	**% total**
No	No	No	268	7.9%
No	No	Yes	36	1.1%
No	Yes	No	40	1.2%
Yes	No	Yes	296	8.7%
Yes	Yes	No	424	12.5%
Total	–	–	1064	31.4%

SP3: Route choice PT. Of the 1'637 SP3 respondents, 326 (19.9%) exhibit non-trading and/or weak-lexicographic behavior. As in SP2, the share of respondents always choosing the same route is larger than in earlier surveys, again likely reflecting the more realistic but narrower attribute ranges.

Table 7: SP3 (route choice PT) non-traders and weak-lexicographic preferences in the raw dataset.

Different alts. chosen?	**Only fastest route?**	**Only cheapest route?**	**# total**	**% total**
No	No	No	80	4.9%
No	No	Yes	5	0.3%
No	Yes	No	12	0.7%
No	Yes	Yes	4	0.2%
Yes	No	Yes	34	2.1%
Yes	Yes	No	191	11.7%
Total	–	–	326	19.9%

SP4: Departure time choice. Of the 785 respondents who completed SP4, 305 (38.9%) are non-traders. This share is much higher for car users (48.0%) than for PT users (26.7%), suggesting greater willingness among PT users to shift departure times. As in the pre-test, choices before the original departure time are selected more often than choices after it, especially among car users, pointing to a stronger disutility of arriving later than originally planned.

Table 8: SP4 (departure time choice) non-traders in the raw dataset.

	RP mode			
SP4 alt.	**Car**	**PT**	**# total**	**% total**
Before peak	103	25	128	16.3
Peak alt. 1	26	20	46	5.9
Current dep. time	43	18	61	7.8
Peak alt. 3	12	11	23	2.9
After peak	31	16	47	6.0
Total	215	90	305	38.9%

To better understand these patterns, Table 9 reports binary logit models for non-trading in SP1, SP2/SP3, and the pooled SP1/SP2/SP3 sample. Very short completion times are strongly associated with non-trading in CAWI. PAPI respondents are more likely to be non-traders in SP1 and in the pooled sample, suggesting either lower engagement or systematic differences in respondent characteristics. Return-home trips show only weak evidence of increasing non-trading in SP1. A longer trip distance reduces the probability of non-trading (due to the increased variation in the attributes), while perceived task difficulty increases it substantially. In SP1, qualitative indicators matter as well: Respondents who report that travel time is unimportant, or who emphasize flexibility, habit, comfort or environment, are more likely to be non-traders.

Overall, non-trading in SP1 is often consistent with strong and stable modal preferences and therefore not inherently problematic. In SP2 and SP3, however, the increase relative to earlier SP surveys is more critical, especially for respondents whose behavior cannot be rationalized by lexicographic preferences. The most plausible explanation is that the narrower attribute ranges in 2025 increased realism but weakened the perceived trade-offs. A smaller number of repeated choice tasks per respondent may have further raised the probability of always choosing the same option. These patterns motivate both targeted data cleaning and the use of model structures that can explicitly account for such behavior.

Table 9: Results of binary Logit models to investigate non-trading behavior in the raw dataset.

	SP1 Coef./(SE)	**SP1: C** Coef./(SE)	**SP2/3** Coef./(SE)	**SP2/3: C** Coef./(SE)	**SP1/2/3** Coef./(SE)	**SP1/2/3: C** Coef./(SE)
PAPI	0.15**		−0.05		0.09**	
	(0.07)		(0.14)		(0.04)	
Dur. per choice $\leq$ 0.6 min.		0.27***		0.40***		0.16***
		(0.07)		(0.13)		(0.04)
RP trip: Return home	0.09*	0.05	−0.11	−0.19	0.05	0.02
	(0.07)	(0.07)	(0.14)	(0.16)	(0.04)	(0.04)
RP mode: PT	−0.35***	−0.41***	−1.06***	−0.97***	−0.39***	−0.41***
	(0.08)	(0.09)	(0.19)	(0.21)	(0.05)	(0.06)
RP mode: Walk	0.29***	0.22**	−0.44	−0.51	1.20***	1.08***
	(0.09)	(0.10)	(0.41)	(0.48)	(0.07)	(0.08)
RP mode: (E-)Bike	0.68***	0.71***	−0.74***	−0.81***	0.47***	0.47***
	(0.11)	(0.12)	(0.25)	(0.29)	(0.05)	(0.06)
Crowfly dist. / 100	−0.69***	−0.40**	−0.79**	−0.78**	−0.61***	−0.43***
	(0.18)	(0.21)	(0.38)	(0.43)	(0.12)	(0.13)
Difficulty = max.	0.73***	0.63***	0.53**	0.64**	0.40***	0.34***
	(0.17)	(0.21)	(0.24)	(0.29)	(0.08)	(0.10)
Time **not** important	0.25***	0.32***	0.55***	0.44***	0.16***	0.18***
	(0.08)	(0.09)	(0.14)	(0.17)	(0.05)	(0.05)
Flexibility important	0.33***	0.33***	−0.10	−0.05	0.15***	0.15***
	(0.06)	(0.07)	(0.14)	(0.16)	(0.04)	(0.05)
Habit important	0.38***	0.38***	0.24*	0.24*	0.21***	0.23***
	(0.08)	(0.09)	(0.14)	(0.16)	(0.04)	(0.05)
Comfort important	0.41***	0.43***	0.33***	0.36***	0.21***	0.23***
	(0.07)	(0.08)	(0.14)	(0.15)	(0.04)	(0.05)
Environment important	0.35***	0.42***	−0.21	−0.26	0.17***	0.19***
	(0.08)	(0.10)	(0.19)	(0.23)	(0.05)	(0.05)
Number of parameters	13	13	13	13	13	13
Number of respondents	5988	4612	5035	3920	6181	4736
$\mathcal{LL}(0)$	−4150.57	−3196.79	−3490.00	−2717.14	−7640.56	−5913.93
$\mathcal{LL}$(model)	−3585.72	−2793.68	−1138.62	−884.47	−7004.14	−5424.75

Cluster-robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

5 Separate models for each data/experiment type

Table 10 reports preliminary choice models for each data type based on the raw dataset (for summary statistics, see Appendix, Table A.1 and Table A.2), estimated in the statistical software *R* using the *mixl* package (Molloy *et al.*, 2021). RPSP denotes the pooled model estimated on RP mode choice, SP1 mode choice, SP2 car route choice and SP3 PT route choice (for more information on pooled model estimation, see e.g. Train, 2009; Schmid *et al.*, 2021). SP4 is estimated separately. The estimation method and utility specification is described in the Appendix, Section A.1.1 and Section A.1.2.

5.1 RP: Mode choice

Most key coefficients are highly significant and have the expected signs. This is noteworthy because RP data alone often provide only limited variation in attributes and strong correlations between them. In particular, the travel cost coefficient is negative and highly significant, indicating that the revised construction of car and PT costs successfully increased attribute realism and identifiability.

PT transfer time is small and insignificant once the number of transfers is controlled for, while the latter has the expected negative effect. The crowding and headway coefficients appear plausible, although both likely still contain a certain RP-specific artifact component, since crowding and headway partly proxy departure time, service quality and accessibility. Car travel time sensitivity is clearly larger than PT travel time sensitivity, which is common in RP-only models. Walking and cycling exhibit the largest time sensitivities, again consistent with previous findings.

Table 10: Estimation results: Choice models for each data/experiment type (raw dataset; SP survey 2025).

	RP Coef./(SE)	**SP1** Coef./(SE)	**SP2** Coef./(SE)	**SP3** Coef./(SE)	**RPSP** Coef./(SE)	**SP4** Coef./(SE)
α_C	−1.16***	−0.24***			−0.46***	
	(0.14)	(0.09)			(0.11)	
+ $\alpha_{C,SP1}$					0.16	
					(0.11)	
+ $\alpha_{C,\text{PAPI}}$		0.15**			0.18*	
		(0.08)			(0.10)	
α_W	0.59***	1.71***			1.47***	
	(0.18)	(0.12)			(0.10)	
+ $\alpha_{W,SP1}$					0.49***	
					(0.13)	
+ $\alpha_{W,\text{PAPI}}$		0.21*			0.26*	
		(0.12)			(0.15)	
α_B	−1.43***	0.27***			−0.57***	
	(0.14)	(0.09)			(0.10)	
+ $\alpha_{B,SP1}$					0.77***	
					(0.09)	
+ $\alpha_{B,\text{PAPI}}$		−0.08			−0.11	
		(0.10)			(0.13)	
$\alpha_{\text{SP2 alt. 1}}$			0.07***		0.04***	
			(0.02)		(0.01)	
+ $\alpha_{\text{SP2 alt. 1, PAPI}}$			0.12***		0.06**	
			(0.04)		(0.02)	
$\alpha_{\text{SP4 alt. 1}}$						−0.89***
						(0.18)
+ $\alpha_{C,\text{SP4 alt. 1}}$						1.03***
						(0.24)
$\alpha_{\text{SP4 alt. 4}}$						−0.39***
						(0.11)
+ $\alpha_{C,\text{SP4 alt. 4}}$						−0.56***
						(0.18)
$\alpha_{\text{SP4 alt. 5}}$						−1.32***
						(0.20)
+ $\alpha_{C,\text{SP4 alt. 5}}$						0.52*
						(0.27)
β^{tc}	−0.22***	−0.13***	−0.22***	−0.14***	−0.13***	−0.06**
	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
μ^{pc}		−0.73***			−0.71***	
		(0.04)			(0.05)	
μ^{mp}		−0.21	−0.44***	−0.28	−0.42***	
		(0.16)	(0.05)	(0.17)	(0.04)	
μ^C						−0.52
						(0.35)
$\beta_{C,traveltime}$	−3.99***	−1.96***	−7.01***		−3.66***	−1.55*
	(0.53)	(0.14)	(0.32)		(0.24)	(0.86)
$\beta_{C,parktime}$		−3.15***			−4.21***	
		(0.66)			(0.86)	

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Table 10 – *Continued on following page*

	RP Coef./(SE)	**SP1** Coef./(SE)	**SP2** Coef./(SE)	**SP3** Coef./(SE)	**RPSP** Coef./(SE)	**SP4** Coef./(SE)
$\beta_{C,accesstime}$		−0.06			0.26	
		(0.46)			(0.57)	
$\beta_{PT,traveltime}$	−3.19***	−2.17***		−3.14***	−2.95***	
	(0.40)	(0.13)		(0.20)	(0.18)	
$\beta_{PT,transfertime}$	−0.84	−0.59**		−3.43***	−2.61***	
	(1.04)	(0.28)		(0.29)	(0.25)	
$\beta_{PT,accesstime}$	−2.41***	−2.57***		−3.14***	−2.85***	
	(0.45)	(0.22)		(0.20)	(0.20)	
$\beta_{PT,transfers}$	−0.20***	−0.08***		−0.20***	−0.12***	
	(0.07)	(0.03)		(0.03)	(0.02)	
$\beta_{PT,headway}$	−3.04***	−0.89***		−1.29***	−1.20***	
	(0.20)	(0.05)		(0.06)	(0.08)	
$\beta_{PT,crowding2}$	−0.50***	−0.03		−0.19***	−0.20***	−0.02
	(0.07)	(0.03)		(0.07)	(0.03)	(0.09)
$\beta_{PT,crowding3}$	−0.24***	−0.30***		−0.74***	−0.46***	−0.67***
	(0.08)	(0.04)		(0.07)	(0.04)	(0.15)
$\kappa_{PT,tt,crowding3}$				0.11**	0.19***	
				(0.05)	(0.04)	
$\beta_{W,traveltime}$	−6.99***	−6.04***			−7.28***	
	(0.51)	(0.25)			(0.46)	
$\beta_{B,traveltime}$	−6.10***	−5.08***			−6.15***	
	(0.31)	(0.19)			(0.33)	
ω_{RP}					0	
ω_{SP1}					−0.21***	
					(0.05)	
ω_{SP2}					0.95***	
					(0.15)	
ω_{SP3}					0.12	
					(0.08)	
$\kappa_{\text{scale,PAPI}}$			−0.11**	−0.04	−0.08**	
			(0.04)	(0.04)	(0.03)	
Number of parameters	14	21	6	13	33	13
Number of observations	24124	35343	20091	9724	89282	4653
Number of respondents	7757	5988	3398	1637	7757	785
$\mathcal{LL}(0)$	−26106.08	−37144.25	−13926.02	−6740.16	−83916.52	−7488.71
$\mathcal{LL}(\text{model})$	−18455.91	−29007.90	−11998.48	−5350.72	−65352.55	−7114.72

Note: Time attributes are in hours. C = car; PT = public transport; B = (E-)Bike; W = walk.
Note: Rows with coefficients where all |t-values| < 1 are excluded from the table for better readability.
Cluster-robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

5.2 SP1: Mode choice

Most coefficients in SP1 are highly significant and show the expected signs. Car and PT travel time coefficients are very similar, implying similar values of travel time (VTT).

The model also points to some systematic differences between CAWI and PAPI respondents: PAPI respondents have significantly higher constants for car and, weakly, for walking. Regarding costs, dynamic pricing is perceived somewhat less negatively than ordinary travel cost, though not significantly, while parking costs are perceived substantially less negatively. Parking search time shows a strong dis-utility, whereas access/egress time to and from the parked car is not significant, likely because its levels are fixed.

PT-related effects are generally plausible. Transfer time remains insignificant, access/egress time is valued more strongly, headway less strongly, and crowding now displays the expected ranking, with the highest crowding level being more negative than the medium one.

5.3 SP2: Route choice car

The SP2 model confirms that respondents tend to prefer the left alternative slightly more often, consistent with the non-trading diagnostics. Travel time and cost are both estimated precisely and with the expected signs. Dynamic pricing is perceived less negatively than ordinary travel cost, with a multiplier implying about 44% lower sensitivity. In addition, PAPI respondents exhibit a significantly lower scale, i.e. more random choice behavior, which is consistent with the stronger non-trading patterns observed for PAPI elsewhere.

5.4 SP3: Route choice PT

All main effects in SP3 are highly significant. In contrast to RP and SP1, transfer time is now of similar magnitude as in-vehicle and access/egress time, which is plausible in a route choice context where these dimensions vary more transparently. The dynamic pricing multiplier indicates a lower sensitivity than for ordinary travel costs, though smaller in magnitude than for SP2. Unlike in SP2, no significant scale difference is found between CAWI and PAPI respondents. Finally, a crowding multiplier shows that travel time under high crowding is significantly more burdensome than under low crowding.

5.5 RPSP: Pooled estimation of RP, SP1, SP2 and SP3

The pooled RP/SP model confirms the main findings from the separate models and illustrates the benefit of combining RP and SP data. The estimated coefficients mostly lie between those of the separate models and are highly significant, with the expected signs and plausible orders of magnitude. Particularly important is the positive SP1 mark-up for (E-)Bike, reflecting the substantially higher bike choice frequency in SP1 than in RP.

The scale parameters are also informative: Relative to RP, the unlabeled route choice experiments exhibit higher scale and therefore lower error variance, which is consistent with the idea that route choice depends more directly on observed attributes. Mode choice, especially in SP1, is affected more strongly by unobserved factors such as comfort, familiarity or convenience, resulting in more unexplained heterogeneity.

5.6 Preliminary valuation indicators

Table 11 shows the preliminary valuation indicators for the raw dataset. It should be emphasized that the values reported in Table 11 should be interpreted with caution, as they are derived from relatively simple model specifications, not weighted by individual or trip characteristics and representative only of the sample averages in the respective estimation datasets. Once relevant covariates such as trip purpose and trip distance are incorporated, and the estimates are re-weighted to reflect the representative MTMC population, the resulting values are expected to change.

Importantly, the current values correspond to the average trip distances in the estimation sample, which are larger than the representative values. Knowing that VTT tend to increase for longer distances, these values have to be seen as a preliminary benchmark, to which the results of more advanced models will be compared (e.g., including non-linear distance interaction effects; see e.g. Mackie *et al.* (2003)). Population-weighted VTT based on behaviorally richer choice models and the data from the MTMC (including weights) will be investigated in a follow-up project and should not be taken from this report.

The VTT for car in SP2 (31.9 CHF/h) is noticeably larger than in RP (18.1 CHF/h) and SP1 mode choice (15.1 CHF/h), which is a well-documented finding in the literature (e.g. Hensher, 2001). Car route choice focuses only on travel time and cost between otherwise similar alternatives. Differences in travel time are more salient and directly comparable, leading to higher VTT. In mode choice, differences in travel time are bundled with other attributes and unobserved factors (comfort, flexibility, reliability, etc.). These other factors partly absorb utility, so the trade-off between time and money appears smaller. Also, mode choice might involve unfamiliar alternatives, leading to lower VTT and higher noise (e.g. Louviere *et al.*, 2000; Cherchi and de Dios Ortúzar, 2006).

The VTT for PT in SP3 (22.4 CHF/h) is also higher than in RP (14.5 CHF/h) and SP1 mode choice (16.7 CHF/h), although the difference is smaller than for car route choice. As mentioned above, since in SP3 many other factors partly absorb utility, the trade-off between time and money becomes less pronounced.

Table 11: Preliminary valuation indicators (value of travel time; VTT, and willingness-to-pay; WTP) in the raw dataset.

Attribute	**RP**	**SP1**	**SP2**	**SP3**	**RPSP**	**SP4**
VTT car [CHF/h]	18.1	15.1	31.9	–	28.2	*51.7*
VTT PT [CHF/h]	14.5	16.7	–	22.4	22.7	–
VTT walk [CHF/h]	31.8	46.7	–	–	56.0	–
VTT bike [CHF/h]	27.7	39.1	–	–	47.3	–
WTP park. time car [CHF/h]	–	24.2	–	–	32.4	–
WTP access time car [CHF/h]	–	*0.5*	–	–	*−2*	–
WTP transfer time PT [CHF/h]	*–3.8*	4.5	–	24.5	20.1	–
WTP access time PT [CHF/h]	11.0	19.8	–	22.4	21.9	–
WTP transfers PT [CHF/#]	0.9	0.6	–	1.4	0.9	–
WTP headway PT [CHF/h]	13.8	6.8	–	9.2	9.2	–
WTP crowding level 2 [CHF/unit]	2.3	*0.2*	–	1.4	1.5	*0.33*
WTP crowding level 3 [CHF/unit]	1.1	2.3	–	5.3	3.5	11.2

Note: *Italic*: Effect not significant at 5%-level.

Finally, the VTT and WTP in the pooled RP/SP model lie somewhere in between/in the range of the values in the previous models. The VTT for car exhibits a value of 28.2 CHF/h, with its preliminary value being noticeably larger than in previous SP surveys (usually below 20 CHF/h). The VTT for PT (22.7 CHF/h) exhibits a clear gap of about 5.5 CHF/h to the one for car.

5.7 SP4: Departure time choice

Results indicate that in case of PT, only the crowding level exhibits a strongly significant effect, while for car, both travel time and cost – while now exhibiting the correct signs – are only marginally significant. Confirming the results of the pre-test, findings indicate that the alternative-specific constants are mostly explaining choice behavior, and that the sample size is still relatively small to draw more solid conclusions.

Testing more profound modeling techniques (e.g., applying a nesting/correlation structure to account for similarities in departure time alternatives) will be part of a follow-up project.

5.8 Summary on preliminary model results

The preliminary choice models for each data/experiment type indicated that the results are consistent and the revised 2025 survey design yields stable and behaviorally plausible estimates.

In the **RP mode choice model**, most key coefficients are highly significant and have the expected signs, which is noteworthy given the usually limited variation and strong correlations in RP data. In particular, the travel cost coefficient is negative and highly significant, suggesting that the revised construction of car and PT costs improved both realism and identifiability. As expected, PT transfer time remains weak (due to high correlation with the number of transfers), while headway and crowding likely still capture some RP-specific biases.

The **SP1 mode choice model** also closely confirms the pre-test. Car and PT travel time sensitivities are very similar, implying similar values of travel time conditional on trip characteristics. Dynamic pricing is perceived somewhat less negatively than ordinary travel cost, while parking costs are perceived substantially less negatively. Parking search time shows a strong dis-utility, whereas car access/egress time is not significant.

In **SP2** and **SP3**, travel time and cost are estimated very precisely. In SP2, respondents show a slight tendency to prefer the left alternative, and PAPI respondents exhibit a lower scale, indicating more random behavior. In SP3, all main effects are highly significant, including transfer time. PT travel time with high crowding is perceived significantly more negative than with low crowding.

The **pooled RP/SP model** confirms these findings and shows that combining RP and SP data yields stable coefficients, plausible trade-offs and informative scale differences across experiment types. Preliminary valuation indicators should be interpreted cautiously, but they are broadly plausible and show the expected pattern that route choice VTT exceed mode choice VTT, especially for car.

Preliminary findings indicate that the VTT are noticeably larger than in previous MTMC-linked SP surveys (ARE, 2017; Weis *et al.*, 2021; ARE, 2024), but more similar to the Swiss value of time study conducted in 2021 (Schmid *et al.*, 2022). To what extent this holds true when accounting for trip and respondent characteristics, and re-weighting according to the MTMC full dataset, will be part of a follow-up project.

6 Conclusions

This paper summarizes the main outcomes of the SP survey 2025 and provides a first assessment of the data quality and plausibility of preliminary choice models. Overall, the findings are encouraging: The combined RP/SP data form a rich empirical basis for further model development and the main effects are identified stable and behaviorally plausible. At the same time, some results require cautious interpretation and will be examined in a follow-up analysis project.

Survey design and methodological improvements: A key design principle of the SP survey 2025 is the close link of SP tasks with the RP reference trip observed by in the MTMC. This pivoting approach ensures individualized and behaviorally realistic choice situations and creates a consistent choice context across individuals.

The 2025 SP questionnaire was designed to remain comparable with the 2021 survey, while incorporating targeted improvements based on the previous SP survey, the internal pre-test, preliminary model results and feedback from the project team as well as accompanying group. The usual SP tasks were retained, but several elements were revised to improve realism, respondent understanding and the usefulness of the data for estimation.

Response rates and sample construction: The total net response rate is 49.3%, while the response rate conditional on successful recruitment is 80.6%. Thus, more than four out of five respondents who agreed to participate completed the SP survey, whereas the main reduction occurred at the recruitment stage. The raw dataset comprises 93'935 choice observations from 7'757 RP respondents, of whom 6'182 completed the SP survey.

Non-trading behavior: A major quality issue in SP data is non-trading behavior. In SP1, the share of non-traders is relatively high, especially among respondents whose reference mode was (E-)Bike and, to a lesser extent, walk. This is not necessarily problematic: Because SP1 is linked to the RP trip, strong existing modal preferences – particularly for shorter-distance trips – can naturally lead to repeated choices of the same mode. Problematic, however, might be those cases where the RP mode differs from the SP1 mode and is the same in all choice situations. The current analysis therefore serves as an empirical basis for exclusion rules related to non-trading.

In SP2 and SP3, non-trading remains much lower in absolute terms, but is still more frequent than in previous SP surveys. The most plausible explanation is the revised experimental design: Compared to 2021, the 2025 tasks use narrower attribute ranges, which increases realism, but weakens the trade-offs between alternatives. As a result, alternatives may appear less distinct in some situations, making repeated choices of the same option more likely. A further contributing factor may be the smaller number of repeated choice tasks per respondent, which increases the probability of observing identical choices.

Models for each data/experiment type and pooled RP/SP model: Overall, the raw dataset provides a strong empirical basis for the subsequent data cleaning and modeling stages. Most key coefficients are highly significant and exhibit plausible signs and magnitudes. The results suggest that the major design changes of the SP survey 2025 were successful. At the same time, the preliminary analysis also highlights some challenges that need to be addressed before estimating more advanced policy-oriented models, such as e.g. the insignificant access/egress time for car or the data pooling with SP4.

Preliminary findings indicate that the VTT are noticeably larger than in previous MTMC-linked SP surveys. To what extent this holds true when accounting for trip and respondent characteristics, as well as re-weighting according to the MTMC full dataset, will be part of a follow-up analysis project.

7 Acknowledgments

The SP survey 2025 would not have been possible without the financial, institutional and technical support of numerous partners. We would like to express our sincere gratitude to all of them.

In particular, we would like to thank the organizations and public authorities that financially supported the survey and/or contributed through their participation in the accompanying group. These include the cantons of Aargau, Basel-Land, Basel-Stadt, Bern, Genf, Graubünden, Luzern, Solothurn, Schwyz, St. Gallen, Tessin, Thurgau, Wallis and Zürich; the Principality of Liechtenstein; the Swiss Federal Office of Energy (BFE); the Swiss Federal Roads Office (ASTRA); the Federal Office of Transport (BAV); Verkehrsbetriebe Zürich (VBZ); Swiss Federal Railways (SBB); the University of Applied Sciences and Arts Northwestern Switzerland (FHNW); the University of Basel.

Their financial support, technical input and continuous feedback on the design, implementation and evaluation of the survey made an important contribution to the quality of the SP survey 2025. We are very grateful for their collaboration and commitment.

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Appendix

A.1 Utility specification and model estimation

A.1.1 Estimation

In the multinomial logit model (MNL), the utilities of the alternatives are described by functions that include a deterministic and a random component (error term). The utility U of alternative i for respondent n in choice situation t is given by

$$U_{i,n,t} = V_{i,n,t} + \epsilon_{i,n,t} \tag{1}$$

where $V_{i,n,t}$ is the systematic/deterministic part and $\epsilon_{i,n,t}$ is a non-systematic, non-measurable component that reflects the person's preferences, any missing variables and the measurement error of the model (Train, 2009). It is assumed that $\epsilon_{i,n,t}$ is independent and identically extreme value type I distributed (standard Gumbel distribution). The equations for $V_{i,n,t}$ are combinations of arbitrary forms of the attributes of the alternatives, the choice situations and the persons. The alternative i is chosen if it has the maximum utility U for person n. Since the error terms $\epsilon_{i,n,t}$ are unknown (but only its logistic distribution), only an assumption about the probability $P(\cdot)$ of choosing an alternative can be made.

All models were estimated in statistical software R using the *mixl* package (Molloy *et al.*, 2021), a specialized software tool developed to estimate flexible choice models for large datasets. The probability that alternative i from the set of all available alternatives $j \in J$ is chosen by person n in choice situation t is given by

$$P(i_{n,t}|\mathbf{\Omega}) = \frac{a_{i,n,t}\text{exp}(V_{i,n,t})}{\sum_j a_{j,n,t}\text{exp}(V_{j,n,t})} \tag{2}$$

where $\mathbf{\Omega}$ describes the vector of all parameters to be estimated and the dummy variables $a_{j,n,t}$ describe the availability of the alternatives. Note that the current models do not include random parameters or error components to account for the panel structure of the data (Train, 2009; Molloy *et al.*, 2021). This refinement will be part of a follow-up project.

All models use cluster-robust standard errors (at the individual-level) to correct the accuracy of parameter estimates, using a post-estimation covariance correction (Zeileis, 2006; Baltagi, 2008). This is based on the fact that there are several, and possibly different numbers of observations T_n per respondent n. The preferences for an alternative or an attribute do not differ from one observation to another, but only between individual decision makers.

The maximum likelihood method is used to estimate the parameters of the utility function (Train, 2009; Molloy *et al.*, 2021). The logarithm of the probabilities of the chosen alternatives (log-likelihood; $\mathcal{LL}$) is maximized for the estimation dataset, so that the modeled behavior reflects the actual behavior as accurately as possible for these parameters. When estimating the model, the properties of the available alternatives (modes of transport and/or routes) are compared and the set of parameters that best represents the entirety of the decisions is determined for the estimation dataset ($\widehat{\boldsymbol{\Omega}}$).

A.1.2 Specification of the systematic part of utility

The systematic part of the utility function for alternative $i \in \{\mathrm{W}, \mathrm{B}, \mathrm{C}, \mathrm{PT}\}$ (i.e., walk, bike, car and public transport in SP1 mode choice) or $i \in \{\mathrm{R1}, \mathrm{R2}\}$ (i.e., in SP2 and SP3 route choice) and person $n \in \{1, 2, ..., N\}$ in choice situation $t \in \{1, 2, ..., T_n\}$ is given by

$$V_{i,n,t} = (1 + \omega_q) \left(\boldsymbol{\alpha}_i \boldsymbol{s}_{i,n,t} + \beta^{tc} \left(x^{tc}_{i,n,t} + (1 + \mu^{mp}) x^{mp}_{i,n,t} + (1 + \mu^{pc}) x^{pc}_{i,n,t} \right) + \boldsymbol{x}_{i,n,t} \boldsymbol{\beta} \right) \tag{3}$$

where in RP and SP1 mode choice, the public transport (PT) alternative was chosen as the reference alternative, while in SP2 and SP3, the second alternative was chosen as the reference alternative. Thus, the parameters α_{PT}, $\alpha_{\text{SP2 alt. 2}}$ and $\alpha_{\text{SP3 alt. 2}}$ of the reference alternatives are normalized to 0.

The utility function $V_{i,n,t}$ thus contains the following components:

- ω_q: Shift of the scale parameter to account for different error variance in the pooled estimation of different datasets (e.g. Train, 2009) $q \in \{\mathrm{RP}, \mathrm{SP1}, \mathrm{SP2}, \mathrm{SP3}\}$ (RP mode choice = reference dataset; $\omega_{\mathrm{RP}} = 0$)
- $\boldsymbol{\alpha}_i$: Vector of alternative-specific constant (ASC) and additional effects on the constant (e.g. $\alpha_{i,\mathrm{SP1}}$; shift if SP1 mode choice; $\alpha_{B,\text{E-Bike}}$; shift in the Bike constant if

an E-Bike is available)

- $\boldsymbol{s}_{i,n,t}$ is a vector of dummy-coded (0 or 1) variables, indicating a specific choice scenario or respondent characteristic (SP1 task dummy, E-bike availability, trip purpose, etc.)
- $x^{tc}_{i,n,t}$, $x^{mp}_{i,n,t}$ and $x^{pc}_{i,n,t}$: Travel, mobility pricing and parking cost attributes
- β^{tc}, $(1 + \mu^{mp})$ and $(1 + \mu^{pc})$: Travel costs sensitivity and multipliers for mobility pricing and parking costs[1]
- $\boldsymbol{x}_{i,n,t}$: Vector of level-of-service (LOS) attributes (e.g., car travel time, PT transfers, etc.; without the cost attributes)
- $\boldsymbol{\beta}$: Vector with parameters of choice attributes (e.g., $\beta_{C,traveltime}$, $\beta_{PT,transfers}$, etc.)

The conceptual difference between the labeled mode choice (RP and SP1) and unlabeled route choice (SP2 and SP3) utilities is that in the former, some (additional) α and β-parameters are estimated alternative-specific (e.g., the effects of travel time for car, PT, walking and cycling), while in the latter, the effects of choice attributes are the same for both alternatives and the constants account for undesirable effects with regard to the order of the alternatives (e.g. Hess *et al.*, 2017).

Thus, the β-parameters are estimated *generically* in case of the *unlabeled* route choice experiments, while they are estimated *alternative-specific* in the *labeled* mode choice datasets (except for travel costs, which are always estimated generically due to microeconomic assumptions on the marginal utility of income; e.g. Small and Rosen, 1981; Jara-Diaz and Farah, 1988; Train, 2009), but ultimately (i.e., in the pooled RP/SP models) correspond to the same parameter. Note, however, that the models allow for distinguishing between different cost sensitivities for different cost components, such as travel cost, mobility pricing and parking costs, which is also necessary due to differences in scaling (e.g., while the costs of parking are at fixed levels, their influence might decrease for longer trip distances).

[1] We use (1 + parameter) in each case so that the hypothesis tests can later be carried out against the value 0 (instead of 1) as standard during model estimation. Also, given the generality of Eq. (3), one should note that e.g. in SP2 and SP3, the multiplier for parking cost disappears, since this cost component is not included.

Table A.1: Summary statistics of RP (N = 7'757; obs. = 24'124), SP1 (N = 5'988; obs. = 35'343), SP2 (N = 3'398; obs. = 20'091) and SP3 (N = 1'637; obs. = 9'724) data.

Variable	**Mean**	**SD**	**Min.**	**Q1**	**Median**	**Q3**	**Max.**
Trip distance (RP; road; km)	9.35	17.73	0.04	1.34	3.34	9.24	333.63
Reference trip distance (RP; road; km)	13.76	22.94	0.10	2.20	5.76	15.64	304.44
Availability car (RP)	0.90	0.29	0.0	1.00	1.00	1.00	1.00
Availability PT (RP)	0.83	0.38	0.0	1.00	1.00	1.00	1.00
Availability walk (RP)	0.61	0.49	0.0	0.00	1.00	1.00	1.00
Availability (E-)Bike (RP)	0.73	0.45	0.0	0.0	1.00	1.00	1.00
Travel time car (RP; min.)	10.89	13.95	1.0	3.00	7.00	13.00	278.00
Travel cost car (RP; CHF)	2.77	5.47	0.1	0.38	0.96	2.69	100.09
Travel time PT (RP; min.)	28.94	25.09	1.0	12.00	21.00	38.00	239.00
Travel cost PT (RP; CHF)	4.20	5.34	0.0	2.20	3.00	4.20	78.80
Transfer time PT (RP; min.)	2.68	3.60	0.0	0.0	0.0	4.0	31.0
Transfers PT (RP; #)	0.66	0.90	0.0	0.00	0.00	1.00	6.00
Access/egress time PT (RP; min.)	10.34	7.61	0.0	5.00	8.00	13.00	159.00
Headway PT (RP; min.)	26.03	16.66	0.0	15.00	26.03	30.00	232.00
Crowding level 2 PT (RP)	0.44	0.50	0.0	0.00	0.00	1.00	1.00
Crowding level 3 PT (RP)	0.16	0.37	0.0	0.00	0.00	0.00	1.00
Travel time walk (RP; min.)	22.99	18.89	1.0	9.00	18.00	33.00	646.00
Travel time bike (RP; min.)	15.30	15.52	1.0	4.00	9.00	21.00	96.00
Availability car (SP1)	0.91	0.29	0.0	1.0	1.0	1.0	1.0
Availability PT (SP1)	0.92	0.27	0.0	1.0	1.0	1.0	1.0
Availability walk (SP1)	0.47	0.50	0.0	0.0	0.0	1.0	1.0
Availability (E-)Bike (SP1)	0.66	0.47	0.0	0.0	1.0	1.0	1.0
Travel time car (SP1; min.)	17.51	19.33	1.0	6.0	12.0	22.0	269.0
Parking search time car (SP1; min.)	2.11	2.04	0.0	0.0	2.0	3.0	10.0
Access/egress time car (SP1; min.)	3.07	1.61	1.0	1.0	3.0	5.0	5.0
Travel cost car (SP1; CHF)	4.96	6.38	0.1	1.2	3.0	6.1	79.1
Parking cost car (SP1; CHF)	3.16	2.50	0.0	0.0	2.0	5.0	7.0
Peak charge car (SP1; CHF)	0.89	2.63	0.0	0.0	0.0	0.3	35.0
Travel time PT (SP1; min.)	22.00	25.41	1.0	5.0	14.0	29.0	283.0
Transfer time PT (SP1; min.)	5.68	6.07	0.0	0.0	4.0	10.0	45.0
Access/egress time PT (SP1; min.)	11.37	7.28	0.0	6.0	10.0	15.0	30.0
Travel cost PT (SP1; CHF)	5.16	7.04	0.0	2.1	3.3	5.4	108.8
Peak charge PT (SP1; CHF)	0.98	2.78	0.0	0.0	0.0	0.5	35.0
Headway PT (SP1; min.)	38.32	28.93	5.0	15.0	30.0	60.0	120.0
Transfers PT (SP1; #)	1.02	0.89	0.0	0.0	1.0	2.0	3.0
Crowding level 2 PT (SP1)	0.33	0.47	0.0	0.0	0.0	1.0	1.0
Crowding level 3 PT (SP1)	0.33	0.47	0.0	0.0	0.0	1.0	1.0
Travel time walk (SP1; min.)	30.95	20.18	2.0	14.0	26.0	46.0	89.0
Travel time (E-)Bike (SP1; min.)	20.15	16.47	1.0	7.0	16.0	30.0	83.0
Travel time route 1 (SP2; min.)	20.45	20.74	1.0	8.0	15.0	25.0	312.0
Travel cost route 1 (SP2; CHF)	5.95	6.77	0.1	2.0	4.1	7.2	88.1
Peak charge route 1 (SP2; CHF)	0.92	2.69	0.0	0.0	0.0	0.3	35.0
Travel time route 2 (SP2; min.)	20.52	20.26	1.0	8.0	15.0	25.0	240.0
Travel cost route 2 (SP2; CHF)	5.95	6.80	0.1	2.1	4.0	7.2	102.2
Peak charge route 2 (SP2; CHF)	0.93	2.68	0.0	0.0	0.0	0.3	35.0
Travel time route 1 (SP3; min.)	20.52	21.47	1	8	14.0	26.0	253.0
Transfer time route 1 (SP3; min.)	5.79	6.81	0	0	4.0	9.0	45.0
Access/egress time route 1 (SP3; min.)	10.31	6.83	0	5	9.0	14.0	30.0
Travel cost route 1 (SP3; CHF)	2.90	4.93	0	0	2.2	3.6	72.7
Peak charge route 1 (SP3; CHF)	1.29	3.31	0	0	0.0	1.1	35.0
Transfers route 1 (SP3; #)	1.00	0.89	0	0	1.0	2.0	3.0
Headway route 1 (SP3; min.)	28.60	24.64	5	10	20.0	30.0	120.0
Crowding level 2 route 1 PT (SP3)	0.34	0.47	0	0	0.0	1.0	1.0
Crowding level 3 route 1 PT (SP3)	0.41	0.49	0	0	0.0	1.0	1.0
Travel time route 2 (SP3; min.)	20.53	21.60	1	8	14.0	26.0	228.0
Transfer time route 2 (SP3; min.)	5.40	5.94	0	0	4.0	8.0	45.0
Access/egress time route 2 (SP3; min.)	10.32	6.86	0	5	9.0	14.0	30.0
Travel cost route 2 (SP3; CHF)	2.94	5.22	0	0	2.2	3.6	72.7
Peak charge route 2 (SP3; CHF)	1.31	3.38	0	0	0.0	1.2	35.0
Transfers route 2 (SP3; #)	1.02	0.89	0	0	1.0	2.0	3.0
Headway route 2 (SP3; min.)	28.94	24.97	5	10	20.0	30.0	120.0
Crowding level 2 route 2 PT (SP3)	0.33	0.47	0	0	0.0	1.0	1.0
Crowding level 3 route 2 PT (SP3)	0.41	0.49	0	0	0.0	1.0	1.0

Table A.2: Summary statistics of SP4 car (N = 448; obs. = 2'659) and PT (N = 337; obs. = 1'994) data.

Variable	Mean	SD	Min.	Q1	Median	Q3	Max.
Travel time car (alt. 1; min.)	21.56	8.88	10.0	16.0	19.0	25.00	79.0
Travel time car (alt. 2; min.)	22.66	9.85	10.0	16.0	20.0	26.00	89.0
Travel time car (alt. 3; min.)	27.60	12.41	11.0	19.0	23.0	34.00	99.0
Travel time car (alt. 4; min.)	23.79	10.31	10.0	17.0	21.0	29.00	76.0
Travel time car (alt. 5; min.)	21.56	8.88	10.0	16.0	19.0	25.00	79.0
Travel cost car (alt. 1; CHF)	7.55	4.24	1.5	4.5	6.4	9.30	28.2
Travel cost car (alt. 2; CHF)	11.47	7.59	1.7	6.3	9.3	14.30	63.9
Travel cost car (alt. 3; CHF)	12.20	7.97	1.7	6.7	9.9	15.40	60.6
Travel cost car (alt. 4; CHF)	11.83	7.48	1.7	6.5	9.8	14.95	55.3
Travel cost car (alt. 5; CHF)	7.55	4.24	1.5	4.5	6.4	9.30	28.2
Travel time PT (alt. 1; min.)	35.20	16.87	12.0	22.0	31.0	45.00	130.0
Travel time PT (alt. 2; min.)	35.20	16.87	12.0	22.0	31.0	45.00	130.0
Travel time PT (alt. 3; min.)	35.20	16.87	12.0	22.0	31.0	45.00	130.0
Travel time PT (alt. 4; min.)	35.20	16.87	12.0	22.0	31.0	45.00	130.0
Travel time PT (alt. 5; min.)	35.20	16.87	12.0	22.0	31.0	45.00	130.0
Travel cost PT (alt. 1; CHF)	1.86	3.16	0.0	0.0	0.0	3.00	26.8
Travel cost PT (alt. 2; CHF)	4.71	5.53	0.0	1.2	3.1	5.40	43.4
Travel cost PT (alt. 3; CHF)	4.95	5.77	0.1	1.4	3.3	5.68	47.5
Travel cost PT (alt. 4; CHF)	4.88	5.68	0.1	1.4	3.2	5.60	47.5
Travel cost PT (alt. 5; CHF)	1.86	3.16	0.0	0.0	0.0	3.00	26.8
Crowding level 2 (alt. 1)	0.03	0.17	0.0	0.0	0.0	0.00	1.0
Crowding level 3 (alt. 1)	0.13	0.34	0.0	0.0	0.0	0.00	1.0
Crowding level 2 (alt. 2)	0.35	0.48	0.0	0.0	0.0	1.00	1.0
Crowding level 3 (alt. 2)	0.20	0.40	0.0	0.0	0.0	0.00	1.0
Crowding level 2 (alt. 3)	0.26	0.44	0.0	0.0	0.0	1.00	1.0
Crowding level 3 (alt. 3)	0.53	0.50	0.0	0.0	1.0	1.00	1.0
Crowding level 2 (alt. 4)	0.37	0.48	0.0	0.0	0.0	1.00	1.0
Crowding level 3 (alt. 4)	0.19	0.40	0.0	0.0	0.0	0.00	1.0
Crowding level 2 (alt. 5)	0.03	0.17	0.0	0.0	0.0	0.00	1.0
Crowding level 3 (alt. 5)	0.13	0.34	0.0	0.0	0.0	0.00	1.0