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The Swiss Household Energy Demand Survey: Panel updates and evidence after eight waves

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Abstract

This paper serves as a comprehensive reference for users of the Swiss Household Energy Demand Survey (SHEDS). SHEDS was conducted annually from 2016 to 2021, followed by two waves in 2023 and 2025; two further waves are scheduled in 2027 and 2029. So far, it provides a panel dataset of eight waves that span a 9-year period. We present recent updates to the panel, including data processing and data quality guidelines, and provide an overview of its evolving structure. In addition, we provide two applications that illustrate the research possibilities enabled by SHEDS. We use the first application to provide a description of how the data can be used to inform an agent-based model. The second application is a descriptive study of the evolution of car ownership patterns showcasing the potential of the survey's longitudinal dimension.

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*The Swiss Household Energy Demand Survey (SHEDS) is a collaborative effort of many researchers. The design is currently coordinated by the authors of the present paper accompanied by Iljana Schubert. Sylvain Weber manages the survey's main coding and online implementation. The dataset has grown to its actual form thanks to about 14,000 respondents, who have thus far completed at least one wave of the survey and a number of them who provided helpful comments and criticisms. The respondents are sampled by Intervista, a Swiss market research institute. We acknowledge financial support from Innosuisse Grant KTI. 1155000154, and from the Swiss Federal Office of Energy's SWEET program. This paper is part of the activities of SWEET CoSi (SWiss Energy research for the Energy Transition: Co-Evolution and Coordinated Simulation of the Swiss Energy System and Swiss Society).

1 Introduction

The Swiss Household Energy Demand Survey (SHEDS) is an open-access dataset[1] that is currently embedded in the SWEET CoSi research consortium (Co-Evolution and Coordinated Simulation of the Swiss Energy System and Swiss Society). CoSi provides a multidisciplinary research program that focuses on the interactions between society and the energy system.[2] SHEDS was developed through a multidisciplinary collaboration among researchers from the (former) Competence Center for Research in Energy, Society, and Transition (SCCER CREST). SHEDS currently includes eight waves with data collected from more than 14,000 respondents.[3]

Weber et al. (2017) and Farsi and Weber (2024) provide more information on the evolution of the survey since its origins in 2016. These previous reports have documented SHEDS' objectives, design, and added value compared to other existing Swiss surveys. These objectives primarily consist of providing empirical bases for (1) understanding household behavior and its evolution, and (2) evaluating the effectiveness of new policy measures and business models aimed at changing individual behaviors (Weber et al., 2017). A more extensive review of the panel structure and new perspectives for integrating behavioral data into energy system modeling is provided by Farsi and Weber (2024). Together, these reports highlight the role of SHEDS in supporting both behavioral research and policy evaluation.

[1] More details, including codebooks and technical documents, are available at: `https://sweet-cross.ch/sheds`.

[2] More information available at: `www.sweet-cosi.ch`.

[3] The respondents are sampled from the Intervista Online Access Panel comprising more than 100,000 persons (see www.intervista.ch/intervista-online-panel).

The present paper has two main objectives. First (in section 2), we offer a practical reference for SHEDS users, presenting an overview of the data, the latest survey updates, and details on data processing and cleaning procedures. Second (in section 3), we provide examples for informing both ongoing research and future efforts to integrate behavioral data into energy system models. To do so, we present two applications using SHEDS: (i) an agent-based model (subsection 3.1) and (ii) a descriptive analysis of the evolution of car ownership in Switzerland (subsection 3.2).

2 SHEDS data: coverage, access and quality

2.1 Survey updates and data coverage

Up to wave 2023, SHEDS has focused on German- and French-speaking regions of Switzerland. Since wave 2025, geographical coverage has been extended to the entire country, including the Italian-speaking region of Switzerland.[4] The panel therefore has nationwide coverage of the Swiss population. This extension strengthens the survey's ability to capture regional diversity and enhances the validity of analyses across regions.

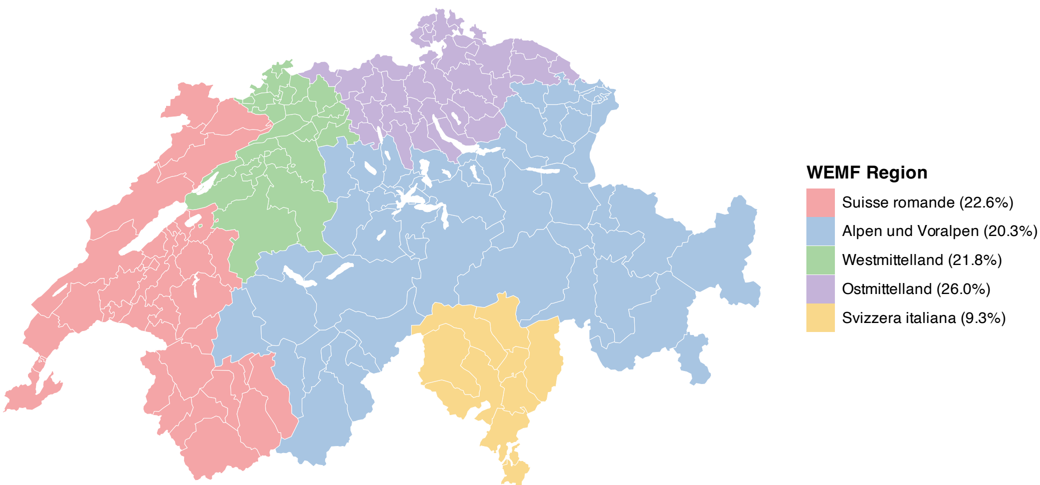
The sampling regions used by the survey company (Intervista) are defined in WEMF/REMP (2017) and shown in Figure 1. These sampling regions are

[4]Note that the Italian-speaking region of Switzerland does not exactly coincide with the canton of Ticino. In fact, it also includes 11 municipalities from the Moesa Region in the canton of Graubünden.

based on linguistic considerations, and hence sometimes differ from Switzerland's seven administrative regions (FSO, 2000).[5]

To date, SHEDS was conducted annually from 2016 to 2021 and biannually thereafter with two waves in 2023 and 2025. Funding is already secured for two further waves in 2027 and 2029. In each wave, former respondents are invited in priority to maximize the returning rate, but attrition is inevitable and the panel is unbalanced. New respondents are therefore integrated in each wave to maintain the sample size stable over time. Moreover, some of

Figure 1: Sampling regions used in SHEDS 2025



Note: The map shows the five sampling regions used in SHEDS. These regions are based on linguistic borders (WEMF/REMP, 2017) rather than cantonal borders. The shares of respondents in wave 2025 of SHEDS are provided in the regions' labels.

[5]As mentioned above, the Moesa Region belongs to the Italian-speaking region (see FSO, 2022) although it is located in the canton of Graubünden (see FSO, 2000). Similarly, the cantons of Valais and Bern are split between French- and German-speaking regions. The cantons of residence are also provided in SHEDS, so that analyses based on administrative regions are also possible. The reasons for defining sampling regions on linguistic borders rather than cantonal borders in a multi-language survey appear obvious.

the returning respondents have gaps of one or several years between waves in which they participated.

Table 1 presents the number of respondents in each wave, distinguishing between new and returning participants, and highlighting the proportion of returning respondents to illustrate the panel's longitudinal dimension. Note that sample size was reduced in 2021 due to budgetary constraints, and increased in 2025 to accommodate the inclusion of the Italian-speaking region of Switzerland.[6] The proportion of returning respondents is therefore naturally lower than in previous waves, although their absolute number is actually slightly higher. This suggests that the study's longitudinal objective is on track, with a substantial share of participants repeating the survey, thereby making it possible to detect changes that have occurred over the years.

The second crucial factor in preserving the longitudinal dimension is maintaining continuity in the data collected. We therefore consistently include and repeat core questions on accommodation, heating, electricity, psychological attributes, environmental attitudes, social context, and energy literacy. Figure 2 provides an overview of the content of SHEDS by display-

Table 1: Number of new and returning respondents, by wave

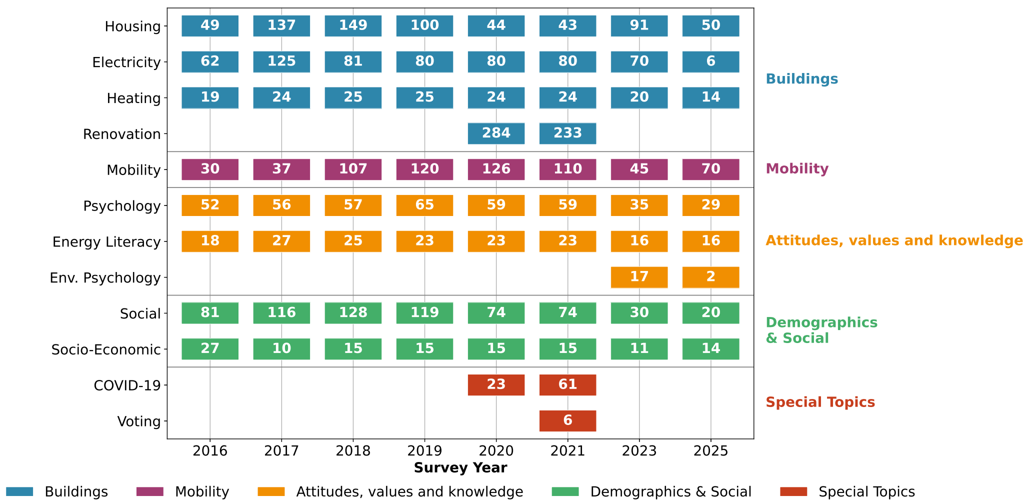
Respondents	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2023**	**2025**
Total	5,015	5,015	5,011	5,021	5,047	4,269	5,038	5,517
New	5,015	2,298	1,543	1,163	1,278	511	1,184	1,619
Returning	0	2,717	3,468	3,858	3,769	3,758	3,854	3,898
Returning share	0%	54%	69%	77%	75%	88%	76%	71%

[6]With 500 respondents, the Italian-speaking region is (voluntarily) over-sampled in comparison to its share in the national population. According to statistics from FSO (2026a), 4.2% of the Swiss population lives in the Italian-speaking region.

ing the number of variables in each section of the survey.[7] The volume of data collected in each category varies across waves, mostly depending on the topic of the survey experiments[8] that are integrated in each wave (see in particular the categories "Renovation" in 2020 and 2021 and "Environmental psychology" in 2023), but also on recent events (see the special topics "COVID-19" in 2020 and 2021 and "Voting" in 2021). One may also note a general decrease in the number of variables between 2021 and 2023, reflecting the decision to reduce the targeted survey duration from 30 to 20 minutes.

While trying to maintain a stable set of core variables, we nevertheless find it necessary to update, add or discontinue certain questions from one

Figure 2: Number of variables available in SHEDS, by wave and category



Note: This Figure shows the number of variables (columns) available in SHEDS datasets in each category. These do not correspond to numbers of questions because each item of a question is coded in its own column.

[7]Note that the number of variables differs from the number of questions, because some questions include multiple items which are then coded in separate variables (columns). Moreover, each respondent may face a different set of questions since a number of questions are displayed conditionally on earlier responses.

[8]Survey experiments occupy a central place in SHEDS; see Weber et al. (2017, section 3.3) and Farsi and Weber (2024, section 2) for further discussion.

wave to another.[9] For instance, considering the rapid evolution in the field of (electric) mobility, we have introduced a new set of questions focusing regarding car ownership (or lack thereof) in wave 2025. One aim is to capture the characteristics and attitudes of car-free households. The survey examines whether these households have previously owned a car and their main reasons for not owning one, including financial constraints, environmental considerations, and reliance on public transport and car-sharing. Additional items assess the likelihood of acquiring a car in the near future, the type of vehicle considered, and perceptions of living without a car. We provide further details regarding these new questions in subsection 3.2 below.

2.2 Data access and file formats

SHEDS data are openly available to academic researchers and can be accessed after fulfilling a few conditions indicated at `https://sweet-cross.ch/sheds`. The data are provided in the following formats:

- CSV files (`.csv`)
- SPSS files (`.sav`)
- Stata files (`.dta`)

CSV files provide only raw data, whereas the files in SPSS and Stata formats include embedded metadata describing variable properties (e.g., ques-

[9]Whenever a question or its response options are modified, the corresponding variable names are also changed. This approach prevents inappropriate aggregation of non-equivalent variables and allows users to decide how best to reconcile the information for the purpose of their analyses.

tion wording and value labels). These metadata streamline data handling and minimize the need to refer to codebooks.[10]

For users working with other statistical software, such as Python or R, dedicated packages allow straightforward data import. For instance, SPSS files can be loaded in Python using the `pyreadstat` library (see Listing 1) and in R using the **haven** package (see Listing 2). Additional detailed examples are provided in the GitHub repository (SiLab, 2025).

Listing 1: Python example loading an SPSS file

```
import pyreadstat # Library to read SPSS files
import numpy as np
file = "/User/olaf/SHEDSYEAR.sav"
df, metadata = pyreadstat.read_sav(f"{file}",
                                   encoding="UTF-8")
```

Listing 2: R example loading an SPSS file

```
library(haven) # Read SPSS files
sheds <- read_sav("/Users/olaf/SHEDSYEAR.sav",
                  encoding="UTF-8")
```

2.3 Data pre-processing

Data pre-processing is essential to ensure the quality and consistency of a dataset. In SHEDS, two types of measures are implemented towards this objective. First, display conditions and constraints are imposed within the

[10]The SHEDS codebooks (SWEET-CROSS Project, 2025) provide detailed documentation of all variables contained in the datasets. One should note that a number of background variables are directly provided by Intervista, rather than collected within SHEDS. As these are not systematically updated, they should be treated with caution.

survey software (Qualtrics), so that obvious mistakes are avoided at the time of data collection. For instance, respondents are not offered the possibility to state that they travel from home to work using their private car if they do not own a car or if they do not work. Instead, they are given the possibility to go backwards and correct their previous answers. New logic conditions are typically introduced whenever potential inconsistencies are discovered in a wave, thereby ensuring data consistency in subsequent waves.[11]

Second, after data collection but prior to releasing the datasets, data cleaning and quality checks are performed with the primary goal of ensuring consistency across waves while preserving as much information as possible. For example, systematic comparisons are conducted on age, ensuring that it increases consistently for each respondent. For transparency, we keep the original `age` variable in the dataset and create a second one `age_corr` in which inconsistencies are resolved by prioritizing the most recent valid entry or by applying pairwise checks when more than two waves are available. We do not eliminate observations, as doing so could reduce the panel's longitudinal value, although data users are obviously free to do so for the purpose of their research.[12]

Two variables must be considered before starting any analyses of SHEDS data: `finished` and `screen`.[13] The `finished` variable indicates whether a respondent answered the survey completely (1) or only partially (0). The

[11]Note that, because of display logic, we occasionally receive complaints from respondents who claim we forgot the answer that apply to them.

[12]Further errors are corrected upon identification and systematically documented in errata files provided alongside the codebooks.

[13]See SHEDS codebooks (SWEET-CROSS Project, 2025) for detailed description of all variables.

`screen` variable reflects the respondent's responsibility for household (financial) decisions. Values 1 and 2 indicate full or partial responsibility, whereas a value of 3 indicates that the respondent is not responsible and was therefore screened out at the introduction stage.[14] A typical starting point for data processing is to filter out respondents with `finished==1` and `screen==3` in order to retain only respondents who answered the full survey until the end. The filtered-out respondents are kept in the original datasets to let data users analyze the sample of all respondents should they so wish. Note also that the number of persons invited to participate in the survey by Intervista is much larger, around three times the actual number of persons who answer (at least partially).

In the datasets, missing or inapplicable responses are coded using negative values rather than software specific conventions such as "NaN" in R or "." in Stata, ensuring consistency across file formats. For example, -1 is typically used for "does not know", and -2 for "does not apply". Using different values for missing answers allows to distinguish between different types of non-response. All such coding rules are documented in the codebooks (SWEET-CROSS Project, 2025) and can also be extracted from the metadata, as mentioned in subsection 2.2.

[14] As several questions relate to household finances, interviewing the latter respondents would likely lead to inaccurate responses.

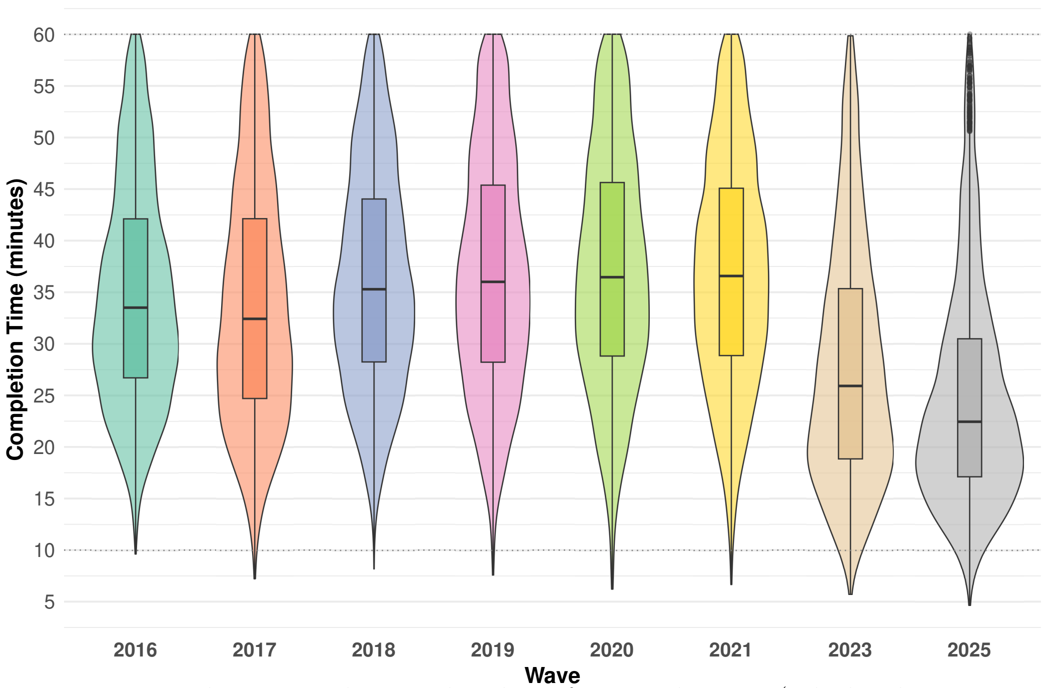
2.4 Quality checks

The target survey duration announced to respondents was 30 minutes until 2021 and 20 minutes from 2023 onward. Figure 3 presents, for each wave, a violin plot with an embedded box plot highlighting the median and interquartile range. To ensure readability, the sample is restricted to survey duration below 60 minutes.[15] The overall shape of the distributions remains largely similar across waves, with a shift reflecting the reduction in the targeted survey duration between 2021 and 2023. The median duration closely aligns with the target duration, and most respondents fall within a reasonable range. Substantial variability in survey duration is expected, as new and returning respondents receive different sets of questions: new respondents complete the full set of core modules, whereas returning respondents answer a reduced set of core questions and are instead assigned to survey experiments. Moreover, depending on respondent characteristics, certain questions are skipped (e.g., for those who do not own a car or for tenants with limited decision-making authority over investments in their home).

A variety of methods and ideas exist for exploring data quality. Here, we follow Leiner (2019) and apply two detection methods for low-quality answers based on completion time and identical responses to multiple items. These methods allow to detect so-called speeders and straightliners. Table 2 presents the number and proportion of respondents falling in these two categories.

[15] Completion times exceeding 60 minutes likely reflect respondents taking one or more breaks during the survey, which are permitted but impossible for us to detect.

Figure 3: Survey duration distribution, by wave



Note: This Figure shows violin plots of survey duration (calculated as the difference between the beginning and the end of the survey; see variable `q_totalduration`) for each wave of SHEDS. Durations above 60 minutes are excluded. The embedded box plot show the medians and interquartile ranges.

Using a 10-minute threshold, we only detect a negligible number of speeders. In 2023-2025, when this threshold corresponds to half of the expected duration, less than 2% of the entire sample fall in this category. When conducted analyses, researchers might want to conduct robustness checks including and excluding these respondents.

We then search for respondents showing signs of straightlining, a response pattern in which the same option is selected repeatedly across items in matrix-style Likert questions. We look at the responses of the longest multi-item question `psy4`, which contains 16 Likert-scale items on psycho-

Table 2: Metrics for low-quality answers detection, by wave

Wave	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2023**	**2025**
Target duration (minutes)	30.0	30.0	30.0	30.0	30.0	30.0	20.0	20.0
Median duration (minutes)	33.5	32.4	35.3	36.0	36.5	36.6	25.9	22.5
Speeders (n)	1	10	1	6	15	8	61	93
Speeders (%)	0.0	0.2	0.0	0.1	0.3	0.2	1.2	1.7
Straightliners (n)	109	120	107	97	140	28	39	67
Straightliners (%)⋆	2.6	2.9	2.6	2.4	3.5	2.6	1.9	1.8

Notes: speeders are defined as respondents with completion times below 10 minutes.

⋆ For straightliners, shares are relative to respondents who received `psy4` item in a given year.

logical attitudes, and flag as straightliners the respondents who provide the same response across all 16 items (as recommended by Leiner, 2019). Across waves, straightlining rates remain relatively stable and low, ranging between 1.8% and 3.5%. Note that these percentages are calculated only among respondents who received this question in the given year rather than among the entire sample.

Two caveats are in order regarding the detection of straightliners. First, the type and number of items must be considered carefully, as in some contexts it may be reasonable for respondents to select the same response across multiple items. Second, the items within multi-item questions are randomized, even though the order of presentation is not included in the datasets to avoid making them unnecessarily large. As a result, detecting straightlining based on a subset of items cannot be conducted using the released datasets alone. Researchers interested in conducting such analyses must therefore request additional information from the managing team.

The above examples are documented in the GitHub repository (SiLab, 2025). We encourage contributions of data-handling scripts to this repository to prevent duplication of effort and to avoid repeatedly redeveloping analyses and coding.

3 Applications

3.1 Agent-based models

Agent-based models (ABMs) can be used to simulate complex systems by representing individual decision-makers (such as households) as autonomous agents who follow behavioral rules and interact with their environment and with each other. Rather than modeling aggregate outcomes directly, ABMs can use heterogeneous micro-level decisions to generate macro-level patterns (e.g., technology adoption or mobility choices). SHEDS data provide empirically grounded information on household characteristics, attitudes, and preferences, which can be used to calibrate these agents. By integrating SHEDS variables into an ABM framework, simulated agents can reflect observed diversity within the Swiss population, allowing the model to reproduce realistic behavioral dynamics and policy responses.

Integrating SHEDS data into an ABM involves identifying the variables required by the model. Once the relevant items are selected, the values can be extracted and processed to match the structure and granularity of the agent population. These adjusted attributes and behavioral indicators should then be integrated into the model in a sensible and consistent way, ensuring that the simulated agents reflect the empirical patterns.

The rest of this section builds on Nguyen and Schumann (2020a), who conducted such an exercise. SHEDS values are incorporated into the calibration of agents within the Behavior-driven Demand Model (BedDeM), an agent-based framework used by the authors to simulate modal choice and vehicle purchase decisions.

The BedDeM framework is composed of an environment in which agents interact and execute actions. An agent consists of five components: *Memory*, *Perception*, *Trigger*, *Decision-making* and *Communication*, as shown in Figure 4. *Perception* accounts for the environment's current state and other agent preferences and combines them with the agent internal state stored in *Memory*. The list of available options is produced and then passed to the *Trigger*. When specific criteria are met, the *Decision-making* component is triggered, building on the Theory of Interpersonal Behavior (see Figure 5). Each option opt is evaluated at a given determinant d based on its expected utility $EU_d(opt)$. This value is computed by aggregating the expected utilities from all ancestor determinants $a \in A$, where each ancestor contributes a normalized utility score weighted by its relative importance w_a. At the first level, these values may be expressed in numerical terms, such as price or travel time, or through ranking functions for qualitative determinants like emotions. These values are then normalized across all available options and combined according to their weights. The resulting expected utility value for each option at determinant d is calculated according to Equation (1).

$$EU_d(opt) = \sum_{a=1}^{A} \frac{EU_a(opt)}{\sum_{o=1}^{O} EU_a(o)} \cdot w_a \tag{1}$$

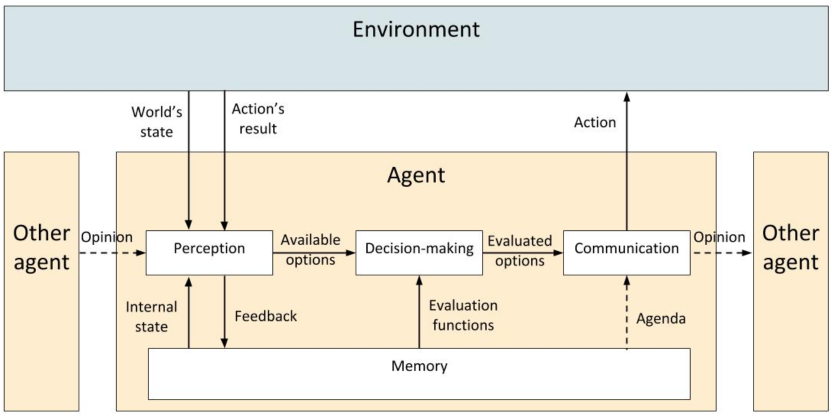
where:

- $EU_a(opt)$ is the utility value of an option (opt) at determinant d.
- A is the set of ancestors of d (i.e., determinants connected with d at the previous level).
- O is the set of all available options.
- w_a is the weight of the ancestor determinant a.

The final decision is communicated back to the *Memory* component and the environment.

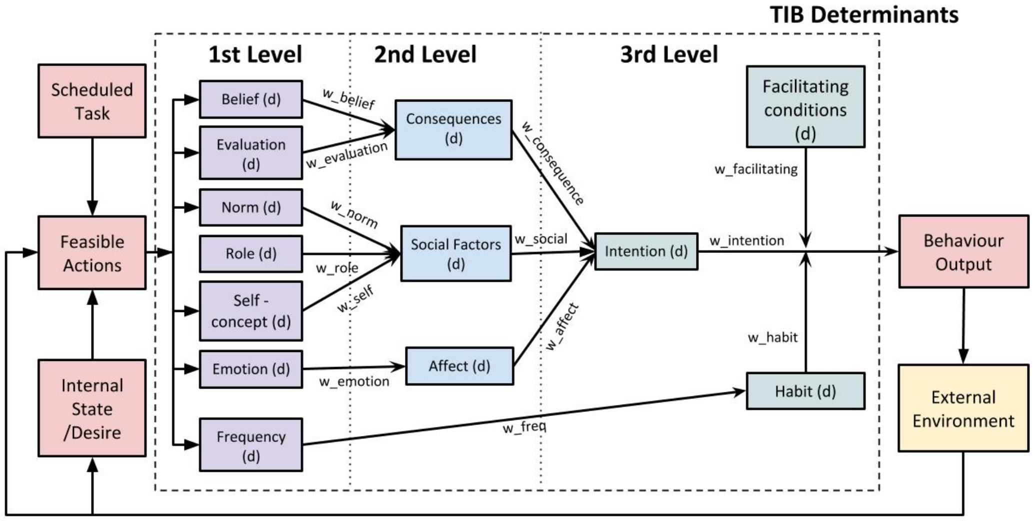
Here we provide a simplified example (based on an example extracted from Nguyen and Schumann (2020b)) showing how parameters such as agent-

Figure 4: Overview of agent's design in BedDeM



Source: Nguyen and Schumann (2020a).

Figure 5: BedDeM decision-making mechanism



Source: Nguyen and Schumann (2020a).

specific weights can be calibrated using values extracted from SHEDS. An agent needs to make a working trip from Sion to Sierre (18 km) and has access to three transportation options: **Car**, **Train**, and **Bike**. These options are listed with predefined values for each determinant (see Table 3). Each determinant has weights (w_a) taken from the SHEDS questions (see Table 4). Starting from the first level, with the **Norm**, **Role** and **Self-concept** determinants, we compute the expected utility of the second-level **Social factors** determinant (see Figure 4). This is achieved by summing the expected utilities of each determinant across all options, resulting into expected utility of each option (see Table 5). These expected utilities are then carried forward to the third-level together with expected utilities of **Consequences** and **Affect**, where they are used to compute the **Intention** determinant.

In the full BedDeM model, the values are assigned in the synthetic population at the level of population clusters rather than at the level of individuals.

Table 3: Definition of first-level `EU` values and determinant weights

Determinant	**Weight**	**Car**	**Train**	**Bike**	$\sum EU_a(o)$
Norm (Social norm)	3	2	1	3	6
Role (environmental friendliness)	2	3	2	1	6
Self-concept (Personal norm)	3	1	2	3	6

Table 4: Role, social and personal norms in SHEDS

Survey question (psy5a): Please rate the extent to which you agree with the following statements:

- **Role beliefs** (`psy5a_3`): Most of my acquaintances expect that I behave in an environmentally friendly manner.
- **Personal norm** (`psy5a_4`): I feel personally obliged to behave in an environmentally friendly manner as much as possible.
- **Social norm** (`psy5a_5`): In the Swiss society, it is usually expected that one behaves in an environmentally friendly manner.

Scale:

○	○	○	○	○
1	**2**	**3**	**4**	**5**
Totally disagree				*Totally agree*

Table 5: Calculation of second-level Social Factors `EU` values

Option	**Norm** $\frac{EU}{6} \cdot 3$	**Role** $\frac{EU}{6} \cdot 2$	**Self-concept** $\frac{EU}{6} \cdot 3$	$\sum EU_{social}$
Car	$\frac{2}{6} \cdot 3 = 1.00$	$\frac{3}{6} \cdot 2 = 1.00$	$\frac{1}{6} \cdot 3 = 0.50$	**2.50**
Train	$\frac{1}{6} \cdot 3 = 0.50$	$\frac{2}{6} \cdot 2 = 0.67$	$\frac{2}{6} \cdot 3 = 1.00$	**2.17**
Bike	$\frac{3}{6} \cdot 3 = 1.50$	$\frac{1}{6} \cdot 2 = 0.33$	$\frac{3}{6} \cdot 3 = 1.50$	**3.33**

Agents do not represent specific individuals, but instead correspond to representative mobility clusters, and the weights associated with these clusters are calibrated accordingly (see Nguyen and Schumann, 2020a).

3.2 Car ownership

Our second application is an empirical investigation of car ownership in Switzerland. We begin by exploring the evolution of hybrid and electric vehicles in Switzerland from 2016 to 2025. We then investigate how demographic characteristics affect car and EV ownership using 2025 data.

Information on car ownership is available from two sources in SHEDS. First, the survey includes a series of questions specifically targeting vehicles. In particular, respondents are asked how many cars are in their household (variable `mob2_1`), and for the household's primary car, additional characteristics are collected, including the engine type (variable `mob3_3`. In multi-car households where the primary car is not electric, respondents are further asked whether any of their vehicles is an EV (variable `mob2_e`). To limit survey duration, returning respondents are asked whether they have changed cars since their last participation; if not, previously collected information – such as purchase date and engine type – is not asked again. For these respondents, car ownership must therefore be constructed by carrying forward the most recently available information across waves until a change is reported.

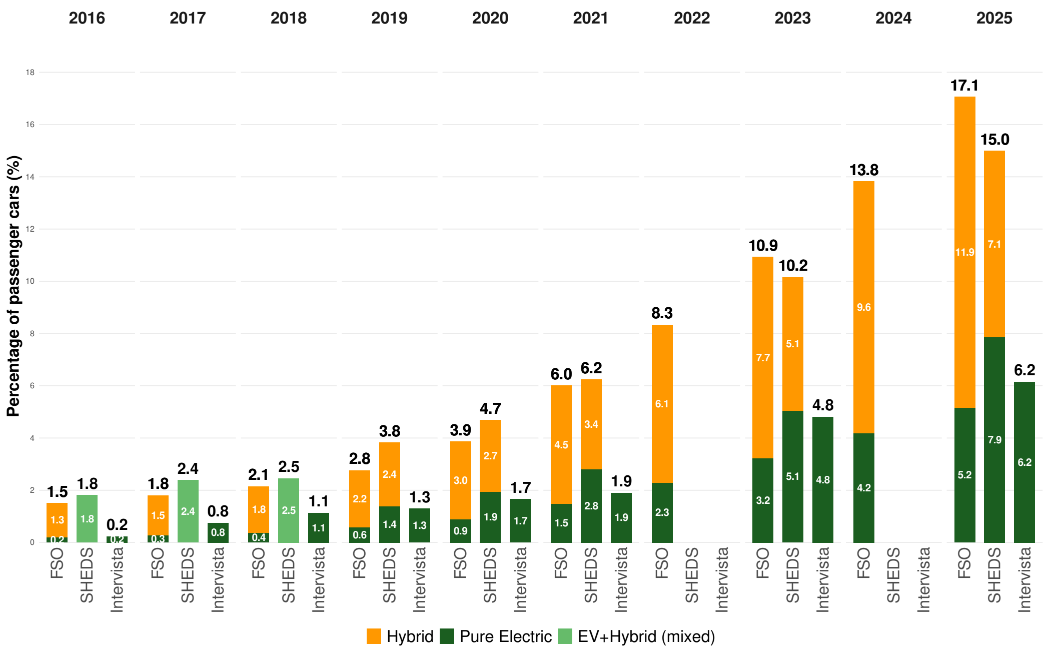
A second source of information on car ownership is provided by background metadata from Intervista, which specify the number of cars in a household (variable md_220) and whether the household owns an EV (variable md_708). However, Intervista's background data are not updated frequently and may therefore not accurately reflect the current situation.

Figure 6 presents the evolution of the share of hybrid and fully electric vehicles among passenger cars in Switzerland from 2016 to 2025. In addition to the two measures derived from SHEDS questions and Intervista metadata, we include data from FSO (2026b) as a benchmark. In both FSO and SHEDS data, hybrid and fully electric vehicles can be distinguished, whereas Intervista data do not provide specific information on hybrid vehicles.[16] As expected, the share of hybrid and electric vehicles increases steadily across all three sources, from a combined share below 2% in 2016 to 15% or even more in 2025. Overall, the combined shares of hybrid and electric vehicles in SHEDS closely match the FSO figures, although their disaggregated shares differ somewhat. One possible explanation is that some respondents misclassify their vehicles as electric when they are in fact hybrid.

We now turn to examining the relationship between socio-demographic variables and car ownership using data collected in SHEDS 2025. Figure 7 presents car ownership (irrespective of engine type) across population groups. It first shows that the majority of Swiss households own at least one car. Among younger adults (18-34), ownership stands at 72%, while for older adults (55+) it reaches 78%. Geographic location seems to strongly influence car ownership: Rural ownership reaches 91% compared to 63% in cities, showing dependence on private vehicles where public transport is less acces-

[16] From 2016-2018, hybrid and electric vehicles were treated as a single category in SHEDS.

Figure 6: Share of hybrid and electric vehicles among passenger cars in Switzerland

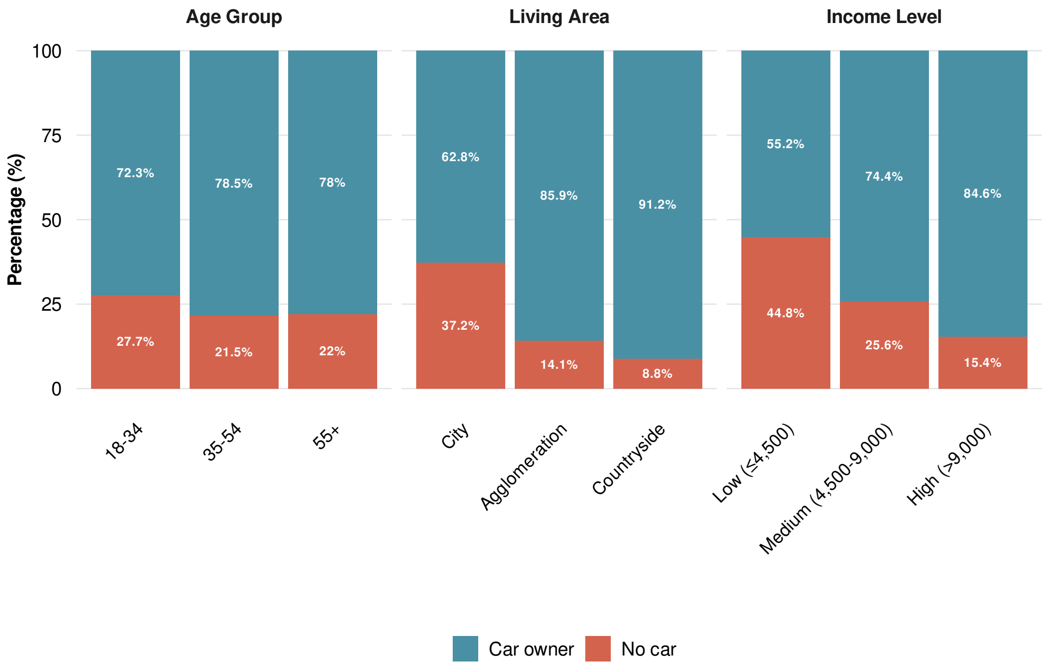


Note: data are drawn from the Federal Statistical Office (FSO, 2026b), SHEDS (variables `mob2_1`, `mob3_3`, and `mob2_e`), and Intervista (variables `md_220` and `md_708`). No SHEDS waves were conducted in 2022 or 2024.

sible. Car ownership also seems to correlate strongly with income, with ownership rates rising from 55% among low-income to 85% among high-income households, suggesting financial reasons as a determinant.

Considering only car owners, Figure 8 provides evidence on the patterns of EV adoption across demographic characteristics. Middle-aged adults show the highest share of EV ownership at 15%, compared to 10% among younger adults and slightly less than 10% among older adults. This suggests that EV adoption is most prevalent among middle-aged households, likely reflecting a combination of greater purchasing power and interest in new technologies. Regional differences reveal higher adoption rates in countryside areas

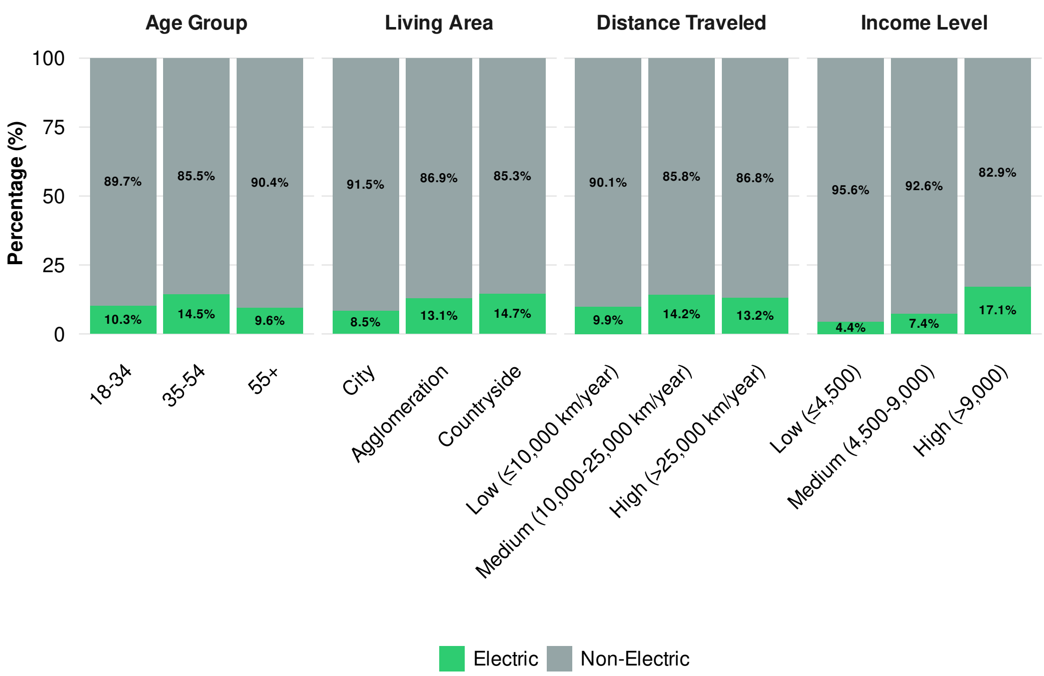
Figure 7: Car ownership, by socio-demographic characteristics



(15%) and agglomerations (13%) compared to cities (9%). Respondents who travel longer distances exhibit slightly higher EV shares than those traveling less than 10,000 km per year. High-income households have a substantially greater share of EVs at 17%, compared to 7% among medium-income and 4% among low-income households.

As a complement to these descriptive findings, we run a multinomial logit regression explaining ownership of non-electric and electric vehicle (vs. not owning a vehicle). The results are displayed graphically in Figure 9. The regression results confirm that age is associated with differences in vehicle ownership: adults aged 35-54 show significantly higher odds of owning EVs compared to the reference group aged 18-34, although the effect for non-electric vehicles is non-significant. Adults aged 55+ also show significantly higher odds of owning both non-electric and electric vehicles. Geographic

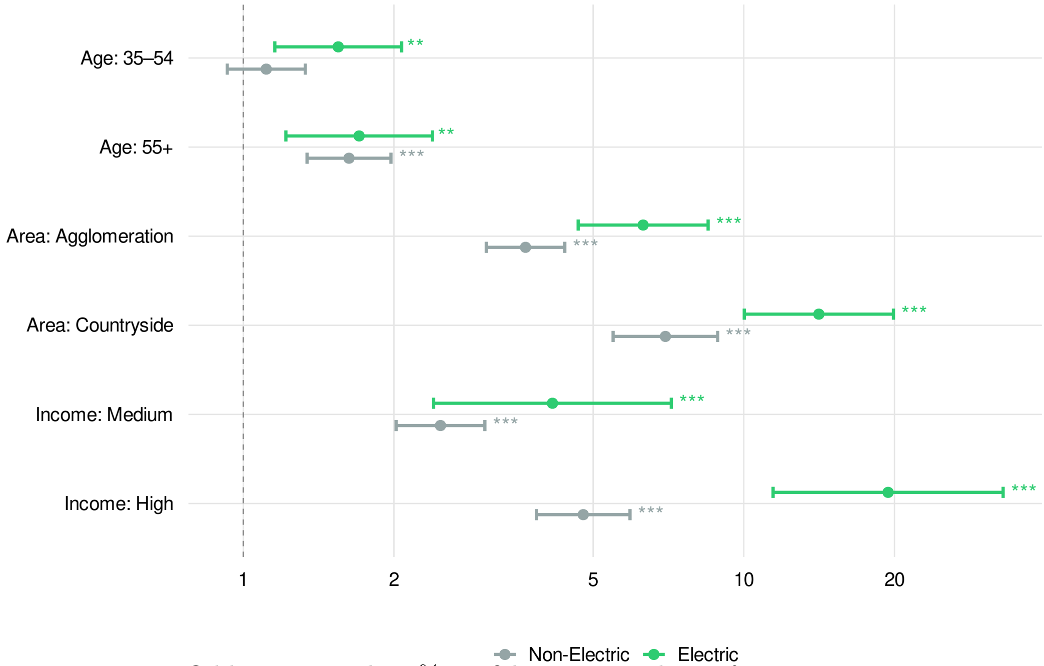
Figure 8: Engine type, by socio-demographic characteristics



location strongly influences both car ownership and vehicle type, with both agglomeration and countryside residents showing substantially and significantly higher odds of owning a car relative to city respondents, with particularly high odds for electric vehicles in rural areas. The regression results indicate a strong effect of income on EV adoption, with both medium- and high-income households exhibiting large and statistically significant odds of owning both non-electric and electric vehicles.

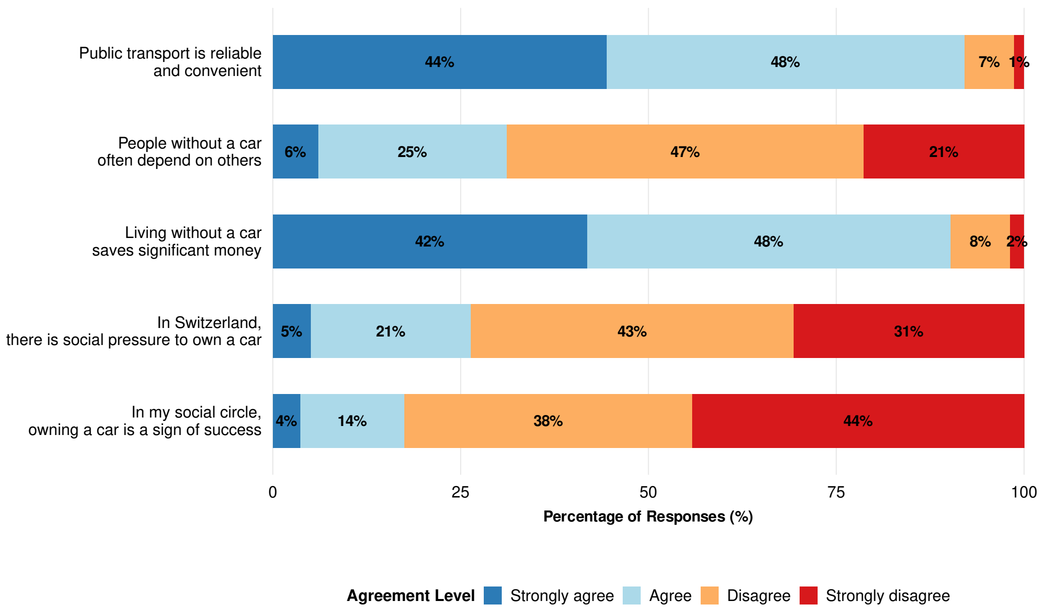
In wave 2025, questions were introduced specifically to examine the reasons why some households do not own a car. Figure 10 illustrates the responses provided by the non-car owners. The factors most frequently cited include the convenience of public transportation and the financial savings associated by not owning a car. Environmental considerations and the desire for greater independence also play a role, although they appear less prevalent. Social pressure appears to play a limited role, with only one-fifth of respondents considering car ownership a sign of success.

Figure 9: Multinomial logit explaining vehicle ownership



Note: Odds ratios with 95% confidence intervals. Reference categories: No car, Age 18-34, City, Low income ($\leqslant$ CHF 4,500/month). $***p <$ 0.001, $**p < 0.01$, $*p < 0.05$; no star indicates a non-significant result ($p \geqslant 0.05$).

Figure 10: Reasons for not owning a car



4 Discussion and future perspectives

In this paper, we describe the most recent updates to the Swiss Household Energy Demand Survey (SHEDS). Most importantly, the Italian-speaking region of Switzerland is included since wave 2025, therefore extending geographic representativeness of the survey to the entire country. We provide information about data accessibility and guidelines to improve the usability of the SHEDS panel. We propose methods to assess data quality and provide processing code in a GitHub repository (SiLab, 2025) for the dataset users, encouraging collaboration and preventing the reinvention of the wheel by multiple groups. We encourage users to contribute and share their code through this platform.

To showcase SHEDS potential, we describe two applications. In the first example, we explain how SHEDS data can be used to calibrate parameters of an agent-based model dedicated to simulate mobility demand in Switzerland. The example shows how the data can be used to cluster individuals based on their preferences, personal values and social norms, thus providing meaningful agent profiles in an energy system model. Second, we demonstrate the panel's temporal dimension using the example of car and electric vehicle ownership. Thanks to its relatively long observation window, SHEDS now makes it possible to investigate changes in attitudes and ownership profiles, offering valuable insights for understanding behavioral dynamics. Such longitudinal information can provide a basis for generating a realistic synthetic population, which can be used for developing behavior models that better reflect the diversity and preferences of Swiss households. The longitudinal dimension can also support energy system models by capturing all types of household behavior, enabling better energy policy analysis and ensuring that future scenarios are grounded in empirical evidence.

To our knowledge, SHEDS has already been used in nearly 50 publications.[17] Two additional waves are planned for 2027 and 2029, which will extend the observation period to more than a decade. This longer time horizon will substantially enhance the panel's analytical potential, particularly for studying behavioral changes, technology adoption, and policy impacts over time. As the longitudinal dimension deepens and the dataset continues to expand in scope and coverage, opportunities for rigorous empirical analysis and model integration will grow accordingly. We therefore expect SHEDS to serve as a foundation for further interdisciplinary collaborations

[17] The complete list of publications based on SHEDS is available here: https://www.overleaf.com/read/bmxtghfhhfcr#c8a935. The list is updated regularly as new publications become available.

and to play an increasingly important role in behavioral energy research and energy-system modeling in Switzerland.

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