Electric vehicle charging strategies among private users

A comparison of self-reported preferences and observed behaviour

Master's thesis in Master Programme Sustainable Energy Systems

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Abstract

This thesis investigates charging strategies among private battery electric vehicle (BEV) owners by comparing self-reported charging preferences with charging behaviour derived from high-resolution logged vehicle data. Survey responses from two measurement occasions (Survey A and Survey B) were combined with complete logged charging data for 273 participants, enabling user-level assessment of how stated charging strategies correspond to realised charging patterns.
A common classification scheme was applied consistently across survey responses and logged data to identify charging strategies. Alignment between reported and observed strategies was quantified using two complementary measures: (1) user-level alignment, reflecting the overall match between a participant's reported and observed strategy set, and (2) strategy-level alignment, showing whether each strategy is reported in the surveys, observed in logged data or both.
Self-reported charging strategies was dominated by need-based and price-aware strategies (40% and 30%, respectively), and observed charging strategies showed a similar distribution (39% and 25%). However, alignment between reported strategies and logged data was limited: full agreement was found for 25% of participants, partial agreement for 45%, and no agreement for 30%. Strategy-level alignment revealed systematic over-reporting of need-based and price-aware strategies, while the need-based strategy was also the most under-reported, indicating that many users exhibited need-based charging behaviour without identifying with the strategy in self-reports.
These findings demonstrate that discrepancies between stated and observed charging strategies cannot be interpreted solely as reporting inaccuracies. Instead, they reflect differences in how users conceptualise and implement charging strategies in practice. The thesis contributes empirical insight into the relationship between stated charging strategies and realised behaviour and highlights the value of integrating survey-based and logged data to understand BEV charging behaviour.

Keywords: Electric vehicles, Charging strategies, Charging behaviour, Private EV users, Logged charging data, Residential charging

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Amanda Gustafsson, Gothenburg, January 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

BEV	Battery Electric Vehicle
EV	Electric Vehicle
OBD	On-Board Diagnostics
PV	Photovoltaic
SCB	Statistiska Centralbyrån
SoC	State-of-Charge

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Indices

i	Index for participant (user)
s	Index for charging strategy

Sets

X	Set of charging strategies reported in the survey
Y	Set of charging strategies identified from logged data
$\varnothing$	Empty set

Metrics

TA	Total agreement indicator between two strategy sets (TA $= 1$ if $X = Y$, otherwise 0).
PA	Partial agreement indicator between two strategy sets (PA $= 1$ if $X \cap Y \neq \varnothing$ and $X \neq Y$, otherwise 0).
NA	No agreement indicator between two strategy sets (NA $= 1$ if $X \cap Y = \varnothing$, otherwise 0).
Overlap	Size of the intersection between two strategy sets, $\lvert X \cap Y \rvert$.
$\text{Score}_{A,i}$	Agreement score for participant i based on Survey A.
$\text{Score}_{B,i}$	Agreement score for participant i based on Survey B.
Improvement_i	Change in agreement score for participant i between Survey A and Survey B.
$\text{Improvement}_{\text{group}}$	Aggregated improvement score across all participants.
$M_{i,s}$	Mismatch indicator for participant i and strategy s, capturing under-reporting (-1), alignment (0), or over-reporting (1).
$R_{i,s}$	Binary indicator of whether participant i reports strategy s in the survey.

$B_{i,s}$	Binary indicator of whether strategy s is observed in logged charging behaviour for participant i.
D	Strategy drift magnitude, defined as the size of the symmetric difference between two strategy sets, $\lvert X \triangle Y \rvert$.
$AR_{i,s}$	Application rate of charging strategy s for participant i.
$N_{i,s}^{\text{match}}$	Number of charging events for participant i that satisfy the criteria of strategy s.
N_i^{charge}	Total number of charging events observed for participant i.

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1

Introduction

The transport sector is a major contributor to greenhouse gas emissions, accounting for approximately one quarter of total emissions within the European Union (European Parliament, 2019). In response to climate targets such as those set out in the Paris Agreement(United Nations Framework Convention on Climate Change, 2015), electrification of road transport has emerged as a key strategy for reducing emissions from a sector that remains highly dependent on fossil fuels. As a result, electric vehicles (EVs) have been adopted at an accelerating pace in recent years, both globally and within Europe and Sweden (European Environment Agency, 2024; International Energy Agency, 2025; Trafikanalys, 2024).

While the rapid uptake of EVs represents an important step towards emissions reduction, large-scale electrification also introduces new challenges for the electricity system. According to Jaramillo et al. (2022), increasing electricity demand from transport requires charging to be managed in order to avoid exacerbating peak loads and increasing system costs. Unmanaged charging behaviour risks undermining some of the potential benefits of transport electrification.

Smart charging is therefore frequently discussed as a means of enabling efficient integration of EVs by influencing when charging occurs. However, the effectiveness of such strategies ultimately depends on how EV owners actually choose to charge their vehicles. Understanding real-world charging behaviour, and the extent to which self-reported charging strategies correspond to observed charging behaviour, is thus a key prerequisite for successful implementation of smart charging concepts. This thesis addresses this need by comparing reported charging strategies with charging behaviour derived from logged data.

1.1 Literature review

Several studies have investigated EV charging behaviour using survey-based approaches, aiming to characterise user preferences, attitudes, and self-reported charging strategies. These studies provide insight into how EV users perceive charging, price signals, and flexibility, but rely on stated rather than observed behaviour.

A study by Chatzouli et al. (2025) investigates residential EV charging behaviour in Denmark, with a particular focus on price awareness, charging flexibility, and attitudes toward smart charging solutions. The study is based on a large-scale survey of 501 EV users capturing charging practices, price awareness, and attitudes towards smart charging. The survey responses were analysed using latent class analysis, which is a statistical method used to identify underlying behavioural profiles within a population. The results reveal three distinct user groups: proactive, active, and inactive. The user groups differ primarily in their degree of price responsiveness and willingness to postpone or schedule charging in response to electricity price fluctuations. A key finding is that a majority of users exhibit some degree of flexibility, while a smaller share consistently charge without regard to prices. The study's main contribution lies in identifying distinct EV user segments based on price awareness, charging flexibility, and attitudes toward smart charging solutions.

In a Norwegian context, Zatsarnaja et al. (2025) examine EV charging patterns and underlying motives among EV drivers in Norway, a country with a highly mature electric mobility market. The study is based on a nationwide survey of 1,005 battery electric vehicle (BEV) drivers, capturing self-reported charging frequency, charging location, charging strategy, and state-of-charge (SoC) levels, complemented by socio-demographic and psychological variables. Latent class analysis is applied to identify distinct charging behaviour patterns, followed by regression analysis to relate group membership to individual characteristics. The results identify three clear charging profiles: daily convenient chargers, battery-exploiting seldom chargers, and occasional battery-friendly planners, where the latter represents the most sustainable and battery-friendly charging behaviour. Charging behaviour is further shown to be associated with experience, usage intensity, and psychological factors. The study provides detailed classification of charging behaviour in a highly mature EV market and highlights the role of psychological and contextual factors in shaping charging routines.

Beyond individual user characterisation, several studies examine the system-level implications of assumed EV charging behaviour. A study by Liao et al. (2023) analyses how different stylised charging behaviours influence charging infrastructure requirements and energy use in a scenario of large-scale BEV adoption. Using an agent-based simulation framework with a synthetic population, the study implements alternative charging behaviours to model spatiotemporal charging demand. The results demonstrate that infrastructure needs and load profiles are highly sensitive to behavioural assumptions, highlighting the importance of accurately representing charging behaviour when aggregating user profiles in system-level models.

Complementing survey-based and system-level approaches, an increasing body of literature analyses EV charging behaviour using empirically logged charging data. These studies provide insight into realised charging patterns, but differ substantially in data granularity, identification of vehicles and users, and availability of contextual information.

Several studies analyse residential charging behaviour using charger-level data collected at private charging points, focusing on plug-in timing, charging duration, power levels, and charging delays (Huang & Ma, 2024; Ziras et al., 2024). While such data provide detailed temporal information on realised charging behaviour, they typically lack vehicle-specific information such as SoC, energy increments, and unique vehicle identifiers. In addition, explicit location information is not always available, requiring charging context to be inferred indirectly based on dominant temporal patterns, such as interpreting overnight charging as residential charging. These limitations may result in charging events from multiple vehicles being associated with the same charger and introduce uncertainty in distinguishing between residential, workplace, and other charging contexts. Nevertheless, charger-level studies provide valuable insight into realised charging behaviour and temporal flexibility, particularly with respect to charging delays.

Empirical studies focusing on public charging infrastructure typically rely on user identifiers associated with RFID tags linked to charging accounts (Weekx et al., 2025). This approach enables longitudinal analysis of charging behaviour at the account level across a defined set of public charging stations. However, such identifiers do not necessarily correspond to a unique vehicle, as a single account may be associated with multiple vehicles over time. In addition, public charging studies are often spatially constrained to specific charging networks, with charging activity outside the observed system not captured.

Some charger-based studies attempt to reconstruct battery state trajectories using partial charger information, such as initial SoC combined with approximations over time (Sørensen et al., 2023). While this extends analytical possibilities when vehicle-level data are unavailable, it also introduces additional assumptions regarding battery behaviour.

Review literature highlights a persistent methodological separation within EV charging behaviour research, where survey-based studies focus on user preferences and attitudes while logged-data studies analyse realised charging behaviour, with limited integration between the two approaches (Shariatzadeh et al., 2025). This separation constrains the ability to assess whether stated charging strategies are reflected in observed behaviour.

The present thesis builds upon a prior study that analysed high-resolution logged driving and charging data to characterise habitual EV usage and charging behaviour at the individual level (Kobayashi et al., 2025). The study focused on identifying recurring mobility and charging routines based on observed driving patterns and charging events, rather than classifying behaviour in terms of explicit charging strategies. Although a survey capturing user-reported driving and charging preferences along with attitudes towards subjects such as vehicle-to-grid was administered within the same project, the study focused on analysing the logged driving and charging data at the individual level rather than linking results from the survey to the logged data.

As a result, the prior study did not assess the relationship between reported charging preferences and observed charging behaviour. Self-reported strategies and logged charging data capture different aspects of charging practices, and reliance on only one of these sources may therefore provide an incomplete picture. Therefore, the present thesis builds upon the prior work by explicitly linking survey responses to vehicle-level charging data, enabling a systematic comparison between stated preferences and empirically observed behaviour.

By combining survey-based preference data and high-resolution vehicle-level charging data, the present thesis addresses this gap by empirically assessing the alignment between reported charging strategies and observed behaviour. The results contribute empirical insight relevant to discussions on how aggregated user profiles are represented in system-level charging and infrastructure modelling.

1.2 Aim of the study

The aim of this thesis is to assess the extent to which different charging strategies are applied among private electric vehicle owners, and to examine discrepancies between self-reported charging strategies and observed charging behaviour derived from logged data.

1.3 Research questions

This thesis addresses the following research questions:

RQ1. Which charging strategies do private electric vehicle owners report in the survey responses?

RQ2. To what extent do self-reported charging strategies align with observed charging behaviour derived from logged charging data?

1.4 Scope, delimitations and limitations

This thesis investigates charging behaviour among private BEV owners in Sweden by combining stated preferences, self-reported behaviour, and observed charging patterns derived from high-resolution logged vehicle data. The analysis focuses on strategy-level characterisations of charging behaviour, enabling comparisons between intended, reported, and observed practices at the individual user level. Survey data collected at two time points are used to capture preferences and self-reported behaviour, while logged data provide empirical insight of actual charging activity during the available observation period. In addition to charging behaviour, contextual information such as electricity contract type and ownership of household energy technologies is available and used at a descriptive level to support interpretation of the results.

The study is deliberately delimited to behavioural comparisons at the charging strategy-level and does not attempt to model optimal charging schedules or assess system-level impacts on the electricity grid. The analysis is restricted to private BEV owners and excludes plug-in hybrid electric vehicles, commercial fleets, and other vehicle categories. Although individual-level information on electricity tariff structures, photovoltaic (PV) system ownership, and stationary battery systems is available, these variables are not incorporated into the main behavioural analysis. Instead, the thesis focuses on identifying and comparing dominant charging strategies across data sources, rather than stratifying or modelling behaviour conditional on these contextual factors. More detailed analyses of how tariffs and household energy technologies influence charging behaviour are therefore left for future work.

Some limitations should be considered when interpreting the results. The study relies on pre-existing survey and logged data collected prior to the present thesis, which limits both the temporal coverage and the set of available variables. In particular, high-resolution household load profiles and PV production curves are not available, preventing direct assessment of self-consumption, household load minima, or on-site solar power generation during charging events. As a result, the identification of certain charging strategies relies on proxy variables rather than direct measurements, introducing uncertainty in the classification and interpretation of solar- and load-oriented charging behaviour. In addition, survey responses are subject to self-reporting bias, which may affect the accuracy of stated preferences and self-reported charging behaviour.

1.5 Additional tools

The analysis and code implementation were carried out using Python and PyCharm. ChatGPT was used as a supportive tool, solely used for language refinement and assistance with code debugging and syntax-related issues. The AI tool was not used to generate text, perform data analysis, or interpret results. All methodological choices, data processing, analyses, and interpretations were carried out by the author, who retains full responsibility for the content and conclusions of this thesis. No sensitive or confidential information was shared with AI tools.

2

Conceptual background

This chapter provides the theoretical context necessary for the thesis, introducing the concept of smart charging and outlining the electric vehicle characteristics considered in the analysis.

2.1 Smart charging and charging strategies

Smart charging is commonly defined as the controlled scheduling of EV charging in time, allowing charging demand to be shifted away from peak load periods and adapted to system conditions such as electricity prices, grid constraints or the availability of renewable energy (Power Circle, 2022). By decoupling charging demand from immediate vehicle arrival, smart charging allows flexibility in when energy is drawn from the electricity system, thereby supporting more efficient system operation and improved integration of variable generation (International Renewable Energy Agency, 2019).

In many applications, smart charging is implemented through centralised control schemes, where charging profiles are optimised based on system-level objectives such as peak load reduction, cost minimisation, or grid stability. However, the effectiveness of such control schemes depends not only on technical infrastructure but also on user behaviour, as charging decisions are ultimately initiated by vehicle owners. In this study, smart charging is not implemented as an active control mechanism. Instead, the focus is on charging strategies as patterns. A charging strategy is here understood as a dominant pattern in how charging is initiated. Strategies are not mutually exclusive, meaning that they may occur at the same time. Multiple strategies can coexist within the same individual. Therefore, when a user expresses a charging strategy, it does not mean that every single charging event follows that strategy. Rather, it means that the pattern occurs frequently enough to be considered meaningful.

2.2 Electric vehicle characteristics

This study focuses exclusively on BEVs. For readability, the term EV is used throughout the thesis to refer to BEVs, unless stated otherwise. Plug-in hybrid electric vehicles and hybrid electric vehicles are not included in the analysis, as their charging behaviour and energy use patterns differ substantially due to the presence of auxiliary combustion engines.

As the analysis centres on charging behaviour rather than detailed vehicle performance, EVs are treated at an aggregated level. SoC is used as the primary indicator of charging need, as it provides a standardised and vehicle-independent measure of remaining battery capacity. While absolute driving range depends on factors such as battery size, vehicle efficiency, and driving conditions, SoC serves as a practical proxy for users' perceived need to charge.

3

Method

3.1 Data sources

This study uses three complementary data sources to capture users' intended, self-reported, and observed charging behaviour. Survey A was administered before the study began and measures participants' self-reported intended charging strategies. Survey B, distributed after the collection of driving and charging data was completed, captures participants' updated self-reported strategies. Logged charging data were collected throughout the study period using an on-board diagnostics (OBD) logging device and represent participants' actual charging and driving behaviour.

Comparing self-reported charging strategies across two survey waves allows for an examination of the stability and consistency of reported strategies over time. As the second survey is conducted after a period of logged charging, this comparison also provides insight into how self-reported strategies may evolve following users' charging experiences.

Analyses are conducted on several population subsets depending on data availability across data sources. In addition, supporting datasets are used to enable strategy identification.

The data used in this study originates from a large-scale study on residential EV driving and charging behaviour (Kobayashi et al., 2025). This thesis constitutes a secondary analysis of that dataset; the primary data collection and preprocessing procedures are described in detail in the referenced study.

In the prior study, participants were selected by Statistics Sweden (SCB) from a national register-based sampling frame of privately owned BEVs in Sweden. The sampling frame was constructed using the Swedish Vehicle Register (SCB, 2025d), the Register of the Total Population (SCB, 2025c), the Database of Household Residences (SCB, 2025a), and the Geographical Database (SCB, 2025b).

The dataset was restricted to passenger BEVs that were privately owned, registered as in traffic, and compatible with OBD-based logging devices. Applying these criteria resulted in a population of 33 260 eligible EVs, representing 55 distinct EV models.

EV owners were invited to participate from predefined combinations of residential area type (non-urban, small town, and large urban areas) and housing type (detached houses and apartment buildings). In total, 4 449 EV owners were invited, of whom 480 accepted the invitation. Participants received an initial survey (Survey A) and a logging device that was connected to the vehicle OBD port to record driving and charging behaviour. After the logging period, participants received a follow-up survey (Survey B).

Following data quality screening in the prior study, the final analysis dataset consisted of 334 EV owners. Participants ranged in age from 23 to 87 years, with an average age of 57 years; 84% of participants were over 40 years old. While the prior study focuses on analyses of logged driving and charging data, the survey data collected from participants are not analysed beyond descriptive background information and are primarily intended for future work. In contrast to the prior study, the present thesis integrates survey responses with vehicle-level logged data, allowing stated preferences and self-reported charging behaviour to be analysed jointly with observed charging patterns.

3.1.1 Survey data

Survey A was conducted prior to participants' use of logging device and aimed to capture their initial charging strategies along with other driving and charging related questions. The survey consisted of 63 questions covering demographic characteristics, vehicle information, charging-related behaviours, driving habits, household context, attitudes toward vehicle-to-grid, and experiences with the existing charging infrastructure. Response options consisted of single and multi selects, Likert scales and free-text responses.

Survey B was administered after participants had returned the logging device after logging was finished, enabling assessment of changes in self-perceived behaviour. Compared to Survey A, several survey items were revised to improve clarity and ensure consistent interpretation across respondents. Survey B consisted of 51 questions covering the same subject areas as Survey A. The second survey thus served to both implement these revisions and to capture potential changes in self-reported attitudes over time.

3.1.2 Logged charging data

The logged dataset consists of timestamped driving, parking, and charging events linked to participant-level identifiers. Data were collected using an OBD device provided by Geotab (Geotab Inc., 2025), following the data collection procedure described in Kobayashi et al. (2025).

The logging device records two primary event types: trip events and parking-related events. A trip event corresponds to periods when the vehicle is in motion, while parking events are defined as periods during which the ignition is turned off and/or the vehicle speed remains at 0 km/h for more than 200 s. Charging events are identified through signals indicating the start or end of AC or DC charging. For each event, variables such as timestamps, event duration, SoC, energy increment, and spatial clustering of locations are available.

To preserve participant privacy, the original geographic coordinates used in the prior study were anonymised prior to analysis. User identifiers were replaced with anonymising IDs, and location information was reduced to categorical flags. Locations were classified into categories such as *home*, *vacation house*, *work*, or *other*, enabling location-based filtering without exposing exact coordinates.

Each participant was assigned a unique identifier linking logged data to the corresponding survey responses. In addition, participants were assigned a categorical identifier representing one of Sweden's electricity bidding zones. As electricity prices are uniform within each bidding zone, this allowed for the integration of spot price and solar irradiance data while maintaining privacy. Although more granular, location-specific irradiance profiles could technically be derived, such modelling was considered outside the scope of this study.

The duration of the logging period varies across participants. The earliest recorded events date back to 11 October 2022, while the most recent events included in this study were recorded on 31 March 2025.

3.1.3 Data quality and preprocessing

Prior to classification, the logged data were preprocessed to ensure data quality and relevance. The analysis focuses on parking events. Trip events are therefore not included as standalone observations in the dataset. Consequently, basic requirements were based on total logging duration and cumulative charging time. Users were required to have at least 90 days of logged data and a minimum of 5 400 minutes of recorded charging activity.

The 90-day requirement was chosen to capture stable charging patterns over time. The minimum charging duration requirement was based on the annual average driving distances for EVs participating in the study. This was translated into an approximate annual charging time using the average energy consumption and average charging power for the population. Applying preprocessing rules for the logged data resulted in reducing the original sample of 384 EVs to the final sample of 314 EVs. Preprocessing the survey data included retaining only the most recent response for each participant in cases where multiple responses were recorded. Detailed exclusion outcomes, including the calculation underlying the minimum charging duration requirement, are provided in Appendix B.1.

3.1.4 Population subsets

The analysis is based on three primary populations derived from survey responses and logged data. Differences in population size arise from two main factors. First, Survey B was administered after the logging period and therefore received fewer responses than Survey A. Second, the population available for analyses involving logged data is reduced due to preprocessing and the exclusion of participants with insufficient or missing logged data.

Let A, B, and L denote three populations, where A represents participants who completed Survey A, B represents participants who completed Survey B, and L represents participants with sufficient logged data.

Analyses were conducted on the intersection sets required for each comparison. By allowing multiple subsets the analysis could be performed while minimizing data loss. The combined populations are defined as

$$A \cap B, \quad A \cap L, \quad B \cap L, \quad A \cap B \cap L.$$

Define the population sizes as

$$N_A := |A|, \quad N_B := |B|, \quad N_L := |L|,$$

and for the combined populations

$$N_{AB} := |A \cap B|, \quad N_{AL} := |A \cap L|, \quad N_{BL} := |B \cap L|, \quad N_{ABL} := |A \cap B \cap L|.$$

The observed population sizes were

$$N_A = 454,\ N_B = 308,\ N_L = 314,\ N_{AB} = 299,\ N_{AL} = 312,\ N_{BL} = 275,\ N_{ABL} = 273.$$

3.1.5 Additional supporting data sources

Along with the three main datasets, this analysis applied additional datasets to support charging strategy implementation. Global irradiance data for the study period were obtained form SMHI's STRÅNG model and used as proxy for solar panel production in the solar-oriented filter (Swedish Meteorological and Hydrological Institute (SMHI), 2025). Historical electricity spot prices were obtained from NordPool and used in the price-aware filters (Nord Pool, 2025).

3.2 Strategy implementation

This section describes how strategies are implemented across surveys and logged data. While the structure of the data sources differs, a common classification scheme is applied to ensure consistent identification and comparison of strategies. Further, this section outlines how strategies are derived from survey responses and behavioural data, how these representations are harmonised and which preprocessing steps are applied to ensure data quality.

3.2.1 Deriving strategies from survey responses

The primary survey item used for strategy identification was the question: “What is your main charging strategy at your home location?”. In both Survey A and Survey B, this question did not include strategy labels (e.g., need-based or price-aware). Instead, respondents selected one or more statements describing their charging behaviour such as "I charge upon arrival if the battery level is low".

To enable a consistent classification, a conceptual codebook was developed to map each selected statement to a corresponding charging strategy. The complete mapping of the survey options is documented in Appendix A.1.

As the question was multiple-choice, all selected statements for each respondent were aggregated into an individual strategy set. The set stored two variables, a size (how many strategies) and a composition (what strategies). This strategy set constitutes the basis for subsequent comparisons across surveys and logged charging data. Respondents were further classified as single-strategy or multi-strategy users depending on the number of strategies represented in their response.

Free-text survey items for the primary survey question were extracted and processed manually due to their limited sample size and lack of predefined response categories. During this process, a substantial share of free-text responses referred to charging behaviour occurring outside the home such as: "I do not charge my vehicle at home", "Charging primarily takes place at my workplace", and "My charging strategy is to minimize charging at home and instead use a public charger at a commuter parking lot".

As a result, an additional category, off-home charging, was introduced. Although the original survey question explicitly concerned charging strategies at the home location, the inclusion of this category reduced the loss of otherwise informative responses and enabled a clearer distinction between home-based and off-home charging behaviour.

Secondary survey items capture contextual background variables, including household vehicle ownership, number of BEVs, ownership of PV solar panels, availability of stationary energy storage, and type of electricity pricing contract. These variables are analysed descriptively to characterise the study population and to provide contextual background for the preference–behaviour analyses, but are not used as explanatory variables in the quantitative alignment analysis. Variables with substantial non-response are reported descriptively only and excluded from further analysis due to limited data completeness. As Survey B exhibits a lower response rate than Survey A, differences in reported contextual factors between the surveys are interpreted cautiously and may reflect differential response rather than actual changes at the household level.

3.2.2 Deriving strategies from logged data

The logged data were run through a series of filters constructed to capture behavioural indicators corresponding to the defined charging strategies. The classification of charging behaviour is not uniquely defined and therefore involves a number of methodological choices.

Features derived from the logged data included event-type information (e.g., trip and charging events), temporal features (e.g., start and end times and session duration), battery- and energy-related information (e.g., state-of-charge levels and energy increments), as well as location-based indicators (e.g., home versus off-home charging and home bidding zone). In addition to the available data features, a delay feature was constructed by calculating the time difference between the end of a trip event and the start of the subsequent charging session.

Each filter was constructed to process all available charging events for a single EV and apply strategy-specific rules. The filter rules were constructed to cross-check the information provided by the survey responses. For example, for the price-aware strategy, charging events were evaluated against hourly electricity prices to assess whether charging occurred under favourable price conditions.

After applying the strategy-specific filters to each logged charging event and EV, the total number of minutes that met the criteria for each strategy was aggregated at the EV level. This aggregated time was then divided by the EV's total logged charging time, producing the share of charging time aligned with that strategy (hereafter referred to as the strategy application rate).

A binary indicator was subsequently assigned to determine whether the strategy application rate exceeded the minimum application rate required for the strategy to be considered expressed. Section3.4.4 provides detailed descriptions of both the strategy application rate and the binary indicator. The complete set of filtering rules is summarised in Table3.1, while AppendixA.2 gives detailed motivations and minimum application rate definitions for each strategy.

3.2.3 Strategy classification scheme

The charging strategies considered in this study are derived from survey responses. Each strategy is formulated to allow systematic cross-checking against observed charging behaviour. Table 3.1 summarises the criteria used to identify each strategy in the logged data. Charging is defined as the SoC at the end of the charging session being larger than the initial SoC or a positive change in energy increment.

Table 3.1: Operational definitions of charging strategies. Threshold denotes the minimum rate threshold for each of the charging strategies.

Strategy	**Classification criteria**	**Threshold**
Need-based	Charging at home or at vacation house and SoC at the start of charging event is below 50%.	40%
Price-aware	Charging at home or at vacation house and at an electricity spot price below the daily average.	40%
Solar-oriented	Charging at home or at vacation house and when global irradiance is above 150 W/m^2.	30%
Opportunistic-direct	Charging at home or at vacation house and initiating charge within 10 minutes of arrival. SoC at the start of charging event is above 50%.	30%
Household load-aware	Charging at home or at vacation house. Charging event has to be both initiated and ended within charging window, 22:00 and 05:00.	40%
Off-home	Charging at work or other location	30%
None	Not classifying as any of the other strategies, e.g., need-based, price-aware, solar-oriented, opportunistic-direct, household load-aware, or off-home.	30%

Need-based charging reflects situations where charging is primarily motivated by low remaining battery levels or anticipated driving needs. Price-aware charging captures behaviour oriented towards favourable electricity prices, while solar-oriented charging reflects attempts to align charging with potential on-site solar generation. Opportunistic-direct charging represents immediate charging upon arrival without strong need signals, whereas household load-aware charging reflects temporal coordination with other household electricity use. Off-home charging captures charging behaviour occurring predominantly outside the home environment. Finally, none charging represents charging events not aligned with any of the defined strategy patterns.

3.2.4 Harmonisation across data sources

Although survey responses and logged charging data are fundamentally different in nature, harmonisation was achieved by applying a common strategy classification scheme across all data sources. A conceptual illustration of the harmonisation is presented in Figure 3.1, charging strategies derived from survey responses and logged data are all represented as user-level strategy sets based on the same conceptual definitions. This harmonised representation allows for consistent analysis across intended and observed behaviour, while preserving the distinct characteristics of each data source.

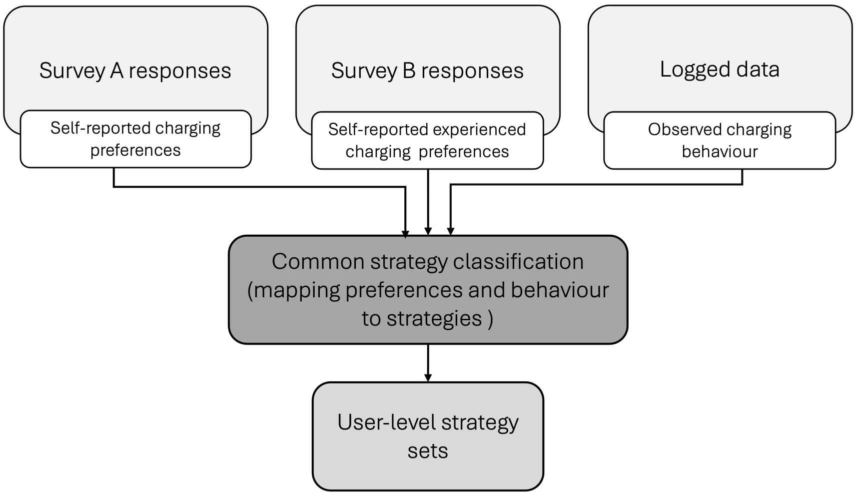


Figure 3.1: Conceptual illustration of how survey-based charging preferences and logged charging behaviour are combined through a common strategy classification and represented as comparable user-level strategy sets.

3.3 Analytical framework and comparison logic

The analysis is structured into four sequential levels capturing self-reported and logged behaviour, as well as their alignment. Survey A and Survey B are analysed as representations of intended and post-use self-perceived charging strategies. Changes in self-perceived strategies are assessed by comparing user-level sets derived from the two surveys. Observed charging strategies are analysed using logged data aggregated at the user level. Assessment of the degree of charging strategy alignment is evaluated by comparing survey-derived strategy sets with data-derived strategy sets.

Through triangulation, each individual is represented with three different values; Survey A, Survey B and their corresponding logged data. These representations allow for insight to their intention, self-perception after experience as well as their recorded behaviour. Triangulation is restricted to individuals with available data across all three representations, ensuring consistent comparison.

3.4 Agreement metrics

This section outlines the agreement metrics used in this study, which quantify the degree of correspondence between self-reported charging strategies and observed charging behaviour. The section distinguishes between different levels of alignment and change, and explains how each metric is applied across the analysis. Finally, the behavioural indicators derived from logged data are described in more detail.

3.4.1 User-level agreement

Since participants could choose between one or more responses in Survey A and Survey B respectively, the number of strategies may vary over time. To capture the level of agreement both across surveys but also between Survey And logged data, the following agreement categories are defined in Eq. (3.1)-(3.3). Let X and Y denote the sets of charging strategies associated with a given participant in two different data sources (e.g., Survey A and Survey B, or a Survey and Logged data).

$$\text{Total agreement} = \begin{cases} 1, & \text{if } X = Y \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

$$\text{Partial agreement} = \begin{cases} 1, & \text{if } |X \cap Y| \geq 1 \ \land \ X \neq Y \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

$$\text{No agreement} = \begin{cases} 1, & \text{if } X \cap Y = \varnothing \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

Total agreement is defined as a full set match, meaning the strategy sets are identical, both in size (how many strategies) and composition (what strategies). Partial agreement is defined as one or more strategies overlapping between sets, but not the full set. Therefore, partial agreement is valid only for sets including more than one strategy. The final category is the no agreement category, defined as no strategies overlapping across sets.

While the agreement categories capture the level of agreement, they do not describe how much the strategy sets overlap. To quantify this, an overlap measure is calculated to assess to what extent two sets match, defined in Eq. (3.4). Overlap counts how many charging strategies are shared between the two sets, regardless of agreement category.

Low overlap values indicate that few strategies are shared, while higher values indicate greater similarity in strategy content between the sets. Overlap is evaluated at the user level as the number of strategies that appear in both sets.

$$\text{Overlap} = |X \cap Y| \tag{3.4}$$

To quantify changes in alignment between surveys A and B relative to behavioural data, an improvement score was constructed. Agreement categories were mapped to numerical values (no agreement = 0, partial agreement = 1, total agreement = 2), allowing each survey to be assigned an individual agreement score. Improvement was defined as the difference between agreement scores in Survey B and Survey A, as formalised in Eq. (3.5).

$$\text{Improvement}_i = \text{Score}_{B,i} - \text{Score}_{A,i} \tag{3.5}$$

The improvement score is bounded by construction and takes values in the interval shown in Eq. (3.6), reflecting the ordinal nature of the underlying agreement scale.

$$\text{Improvement}_i \in \{-2, -1, 0, 1, 2\} \tag{3.6}$$

Group-level improvement was obtained by aggregating individual improvement scores across participants, as defined in Eq. (3.7).

$$\text{Improvement}_{\text{group}} = \sum_{i=1}^{N} \text{Improvement}_i \tag{3.7}$$

3.4.2 Strategy-level agreement

Mismatch measures the correspondence between self-reported charging strategies and observed charging behaviour. For each participant, mismatch is evaluated at the strategy level by comparing reported strategy with the corresponding indicator derived from the logged data, as described in Eq.(3.8). This comparison is performed independently for each strategy within a user's strategy set, allowing mismatch to be assessed on a per-user and per-strategy basis.

The comparison yields three possible outcomes: under-reporting, where a strategy is not reported but is observed in the logged data; over-reporting, where a strategy is reported but not observed; and neutral alignment, where both the self-reported strategy and the behavioural indicator are present. As mismatch is evaluated separately for each strategy, a single participant may simultaneously exhibit both over- and under-reporting across different strategies.

$$M_{i,s} = R_{i,s} - B_{i,s} \tag{3.8}$$

where $R_{i,s} \in \{0,1\}$ indicates whether participant i reports strategy s, and $B_{i,s} \in \{0,1\}$ indicates whether strategy s is observed in the logged data for participant i. The resulting mismatch $M_{i,s}$ measure takes values of -1 (under-reporting), 0 (neutral alignment), or 1 (over-reporting).

3.4.3 User-level change

On a user-level, drift is quantified to capture the magnitude of change in reported charging strategy sets between measurement points. This metric primarily supports comparisons across surveys. Drift is defined based on changes in set composition, such that both the addition and removal of strategies contribute to a shift in the strategy set. Drift is computed as a numerical set-distance measure (Eq. 3.9) and subsequently reported using categorical labels based on predefined thresholds (Eq. 3.10) to improve interpretability. In addition to the magnitude of change, transitions between single- and multi-strategy configurations are monitored. This complementary metric captures whether users remain stable in their strategy complexity over time, or whether their reported behaviour expands or contracts with experience.

$$D = |X \triangle Y| \tag{3.9}$$

$$\text{Drift category}(D) = \begin{cases} \text{No drift,} & D = 0 \\ \text{Small drift,} & D = 1 \\ \text{Moderate drift,} & D = 2 \\ \text{Big drift,} & D \geq 3 \end{cases} \tag{3.10}$$

3.4.4 Behaviour derived match metrics

Behavioural strategies are quantified using two complementary metrics: a strategy application rate and a corresponding Boolean indicator. The strategy application rate captures the extent to which an individual's observed charging behaviour is consistent with a given charging strategy. It is calculated as the proportion of observed charging behaviour that satisfies the criteria of a given strategy relative to the total observed charging behaviour for that individual, as shown in Eq.(3.11).

$$AR_{i,s} = \frac{N_{i,s}^{\text{match}}}{N_i^{\text{charge}}} \tag{3.11}$$

where $AR_{i,s}$ denotes the application rate of charging strategy s for user i, $N_{i,s}^{\text{match}}$ is the number of charging events for user i that satisfy the criteria of strategy s, and N_i^{charge} is the total number of charging events observed for user i.

To enable direct comparison with survey-derived strategy sets, the continuous strategy application rate is transformed into a binary representation using the predefined minimum application rate. Strategies exceeding this threshold are considered expressed by the user and included in the user's observed strategy set, while strategies below the threshold are considered absent. This dual representation preserves information about behavioural strength while ensuring methodological consistency with set-based agreement analyses. Strategy-specific criteria and threshold values are defined consistently across users and are provided in Appendix A.2.

4

Results

4.1 Self-reported charging strategies

This section presents reported strategy preferences in Survey A and Survey B. This includes strategy distributions, changes in participants' responses from A to B, recurring combination strategy patterns and distributions of single or multiple strategy between the two surveys.

4.1.1 Contextual characteristics of survey respondents

This section briefly reports descriptive characteristics of the survey respondents. These results are included to contextualise the subsequent findings and to support qualitative interpretation in the discussion, but they are not analysed further and are not treated as explanatory variables.

Table 4.1 summarises key contextual characteristics of the respondents in Survey A and Survey B. In Survey A, most participants report owning one or two cars, while multi-car households are less common. Regarding EV ownership, the majority of respondents report owning a single BEV, with multiple-BEV households being relatively uncommon.

Solar PV installations are reported by a substantial share of respondents in both surveys. While the proportion of respondents reporting PV ownership is higher in Survey B than in Survey A, the lower response rate in Survey B prevents drawing conclusions about whether this reflects actual changes in installation status or differential non-response.

The presence of stationary battery storage systems is reported by only a small subset of respondents, while a large share did not respond to the question. Due to the high non-response rate, this variable is treated as descriptive only and is excluded from further analysis.

Electricity pricing contracts exhibit considerable variation across respondents. In both surveys, variable monthly and hourly pricing contracts are the most common, while fixed-price and shared multifamily contracts are less prevalent. A small number of responses fall outside the predefined categories and are not interpreted further.

Table 4.1: Contextual characteristics of respondents in Survey A and Survey B

Variable	**Survey A (%)**	**Survey B (%)**
Number of cars in household		
One car	52	–
Two cars	42	–
Three or more cars	6	–
Number of BEVs in household		
One BEV	88.5	–
Two BEVs	11	–
Three BEVs	0.5	–
PV solar installation		
PV installed	31	39
No PV installed	69	61
Stationary battery storage		
Yes	7	–
No	24	–
No response	69	–
Electricity pricing contract		
Shared multifamily contract	16	18
Fixed price	17	13
Variable monthly price	31	32
Hourly price	25	36
Other / free-text / rent included	11	1

4.1.2 Strategy frequency in Survey A and B

Figure 4.1 presents the distribution of reported charging strategies in Surveys A and B. In Survey A, the need-based and price-aware strategies are the most prevalent, reported by 40% and 28% of respondents, respectively. The remaining strategies are reported to a substantially lower extent, all below 10%. It should be noted that the off-home strategy was not included as a predefined survey option and is instead captured exclusively through free-text responses. All strategy shares are calculated based on both single- and multiple-strategy responses.

In Survey B, the preference for the need-based and price-aware strategies increases further, with 42% and 33% of respondents reporting these strategies, respectively. The remaining strategies are again reported at much lower levels, at 10% or below. Both the household load-aware strategy and the off-home strategy exhibit very low occurrence, at 1% each. For the household load-aware strategy, this can be explained by the removal of the corresponding predefined survey option in Survey B, meaning that any responses mapped to this strategy originate solely from free-text responses, analogous to the off-home strategy.

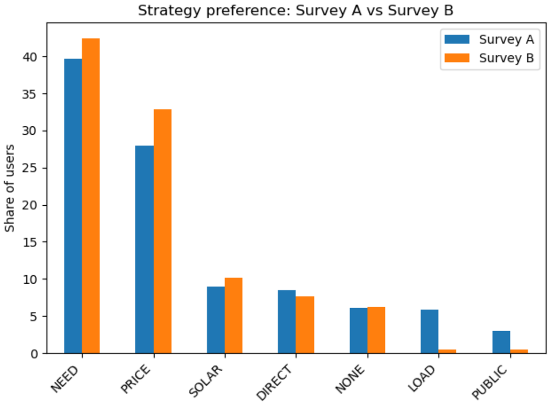


Figure 4.1: Strategy preferences reported in Survey A and Survey B. Abbreviations denote charging strategies (NEED: need-based; PRICE: price-aware; SOLAR: solar-oriented; DIRECT: opportunistic-direct; NONE: none; LOAD: household-load aware; PUBLIC: off-home).

4.1.3 Single vs multi-strategy distributions

Single- and multi-strategy reporting patterns are analysed across surveys to characterise reported strategy complexity. Single-strategy reporting refers to participants selecting exactly one strategy, whereas multi-strategy reporting refers to the selection of two or more strategies. Table 4.2 presents the distribution of single- and multi-strategy responses in Survey A and Survey B. Across both surveys, the majority of participants report using a single strategy. In Survey B, the share of single-strategy reporting is slightly higher compared to Survey A. However, the observed difference between surveys is small and should be interpreted with caution.

Table 4.2: Distribution of single vs multi strategy users for Survey A and B

Survey	Single strategy [%]	Multi strategy [%]
A	68	32
B	72	28

4.1.4 Combination patterns A & B

Common strategy combinations in Surveys A and B are presented in Table 4.3. Certain patterns emerge consistently across participants, suggesting stable and recurring strategy formations. Other combinations are observed less frequently and should be interpreted as indicative rather than conclusive, primarily serving to inform hypothesis generation. Further, only multi-strategy responses are included in the analysis of combination patterns.

The strongest combination pattern is need-based-price-aware charging. This combination appears in both surveys and recurs in 27% of participants in Survey A, increasing to 40% in Survey B.

Weaker patterns include the price-aware–solar-oriented and need-based–solar-oriented combinations, occurring in 15% and 10% of participants in Survey A, respectively.

Table 4.3: Top five strategy combinations in Survey A and Survey B, with corresponding counts and shares. Differences highlight changes in prevalence between surveys. Abbreviations are consistent with the definition made in Figure 4.1.

	Survey A		Survey B		
Strategy combination	Count	Share [%]	Count	Share [%]	Δ Share [pp]
NEED, PRICE	39	27	34	40	+13
PRICE, SOLAR	21	15	15	17	+2
NEED, SOLAR	15	10	11	13	+3
NEED, PRICE, SOLAR	12	8	8	9	+1
LOAD, PRICE	10	7	–	–	–
NEED, NONE	–	–	7	8	–

In Survey B, both combinations increase, with the price-aware–solar-oriented combination rising to 17% and the need-based–solar-oriented combination increasing to 13%.

Combinations are reported as exact matches, meaning that each count refers to the specific strategy set as listed, rather than to the presence of individual strategies across longer combinations (e.g., need–price does not include need–price–solar).

While the most frequent combination patterns are largely consistent between Survey A and Survey B, one notable deviation is observed. In Survey B, the combination of need-based-none charging appears among the five most frequent combinations, replacing the household-load-aware-price-aware combination observed in Survey A. This difference should be interpreted in light of changes to the survey structure, as household load-aware charging was not included as a predefined response option in Survey B. Consequently, the emergence of the need-based-none combination likely reflects differences in available response categories rather than a substantive shift in self-reported charging behaviour.

4.2 Changes in self-reported charging strategies

This section examines changes in self-reported charging strategies between Survey A and Survey B. The analysis focuses on the level of agreement between reported strategy sets, the extent of overlap, changes in strategy complexity, and the magnitude of drift across participants. All results are based on participants with available data in both surveys to ensure a consistent basis for comparison.

Figure 4.2 shows the distribution of agreement categories between surveys A and B. A total of 45% of participants exhibit total agreement, meaning that they reported the same set of charging strategies in both surveys. Partial agreement is observed for 33% of participants, indicating that at least one strategy overlaps between survey responses. The remaining 22% of participants exhibit no agreement, reflecting a complete change in reported strategy sets between surveys.

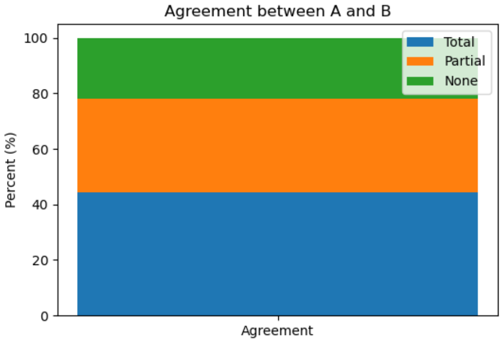


Figure 4.2: Distribution of agreement categories for the comparison between Survey A and Survey B. Total agreement denotes that the user reported exactly the same set of charging strategies in both surveys. Partial agreement denotes that at least one strategy overlaps between surveys, while none denotes that the reported strategy sets do not overlap.

To further characterise similarities between survey responses beyond the agreement categories, Table 4.4 reports the size of overlap between strategy sets reported in Survey A and Survey B. The most common outcome is a single overlapping strategy, observed for 68% of participants, indicating that many respondents retain at least one consistent strategy across surveys while changing others. An overlap of two strategies is comparatively rare, suggesting that complete stability across multiple strategies is uncommon.

Overlap size is calculated for all participants regardless of agreement category. No cases with three overlapping strategies are observed, despite some participants reporting strategy sets of length three.

Table 4.4: Distribution of overlap size between strategy sets reported in Survey A and Survey B. Overlap indicates the number of charging strategies shared between the two surveys, independent of agreement category.

overlap	count	%
0	66	22
1	202	68
2	31	10

While overlap captures similarity in strategy content, changes in the number of strategies provide insight into shifts in strategy complexity. Table 4.5 summarises transitions between single-strategy and multi-strategy responses across surveys A and B. Consistent with the distribution reported earlier, a majority of participants in both surveys indicate a single strategy.

Among participants who selected a single strategy in Survey A, 54% also reported a single strategy in Survey B. In contrast, 13% extended their strategy set by adding one or more strategies, while 18% reduced their reported strategy complexity to a single strategy in Survey B. Finally, 15% of participants reported a multi-strategy configuration in both surveys.

Table 4.5: Transition matrix showing changes in strategy complexity between Survey A and Survey B. Values represent the share of participants reporting single- or multi-strategy configurations in each survey.

	B: Single [%]	B: Multi [%]
A: Single[%]	54	13
A: Multi [%]	18	15

To capture the magnitude of change in reported strategy sets, drift is used to describe how far participants shift in their strategy choices between surveys. Figure 4.3 shows that 45% of participants exhibit no drift in strategy, aligning closely with the total agreement category previously reported in Figure 4.2. A further 25% display a small drift, indicating that one strategy was either added or removed from their strategy set. Moderate and large drift are observed for 23% and 7% of participants, respectively.

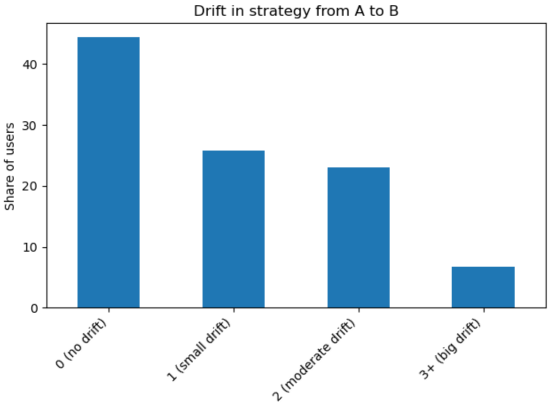


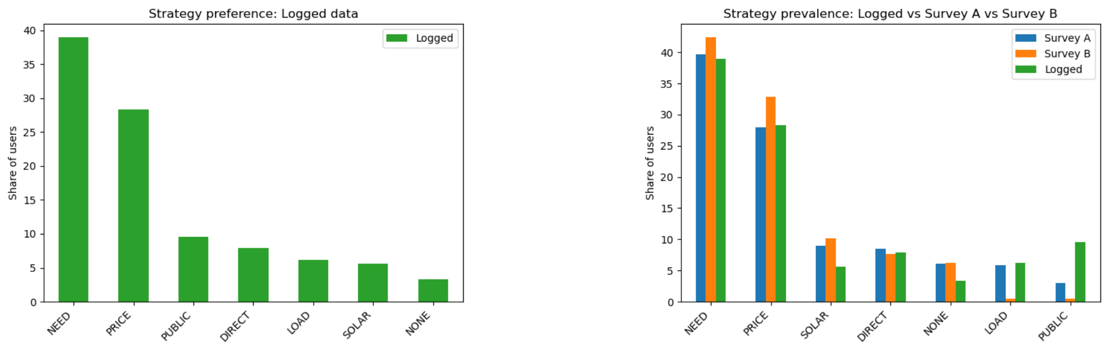
Figure 4.3: Distribution of drift magnitude among participants between Survey A and Survey B. Drift captures changes in reported strategy sets, where both adding and removing a strategy are counted as drift. Drift magnitude is grouped into four categories: no drift, small drift, moderate drift, and big drift.

4.3 Observed charging strategies

This section presents strategy indicators derived from logged charging data. These indicators includes strategy prevalence, application rate distributions, and combination patterns.

4.3.1 Prevalence of each observed strategy

Analysis of strategy prevalence in the logged data indicates a strong dominance of the need-based charging strategy, which is observed for 39% of participants, seen in Figure 4.4. The second most prevalent strategy is price-aware charging, expressed by 25% of participants, while all remaining strategies occur at considerably lower rates, each below 10%. This distribution suggests that a limited number of charging strategies account for the majority of observed charging behaviour, a pattern aligning with the overall distribution of strategies from the two surveys, as seen in Figure 4.4b.



(a) **(b)**

Figure 4.4: (a) Strategy prevalence in logged data. (b) Strategy prevalence in logged data compared to reported preference in Survey A and Survey B. Abbreviations are consistent with the definition made in Figure 4.1.

4.3.2 Charging strategy application rates

The distribution of strategy application rates for each of the strategies are show in Figure 4.5. Only individuals exceeding the minimum application rate are included in the representation. The distributions therefore reflect within-strategy consistency among identified users in how frequently the strategy is applied, rather than overall strategy prevalence in the population. For less prevalent charging strategies, the boxplot representation is comparatively coarse, as these strategies are observed for a substantially smaller subset of users.

Substantial differences in variability are observed across strategies. Off-home charging exhibits the greatest overall dispersion, with a wide interquartile range and long whiskers, with a majority of users apply off-home charging between 40% and 73% of the time. This indicates pronounced heterogeneity in how consistently the strategy is applied among users. Notably, off-home charging is identified based on free-text survey responses.

Both the need-based and the price-aware strategy shows a similarly wide overall range but a more concentrated central distributions. Most participants that classify as need-based users will apply the need-based strategy between 50% and 69% of their total charging time. Most price-based users will apply the strategy between 45% and 66% of their charging time. This suggests greater consistency for the majority of users while still allowing for notable deviations.

Opportunistic-direct charging display a moderately concentrated distribution, with narrower interquartile ranges than the off-home strategy but still considerable spread, where most users apply the strategy between 46% and 68% of the time. In contrast, household load-aware, none, and solar-oriented strategies exhibit lower central distribution levels and comparatively narrower interquartile ranges, indicating that users classified under these strategies tend to apply them less consistently in time. The none charging strategy show outliers at higher application rates. These outliers represent individuals whose charging behaviour aligns strongly with a given strategy, highlighting cross-individual heterogeneity in behavioural consistency rather than measurement error.

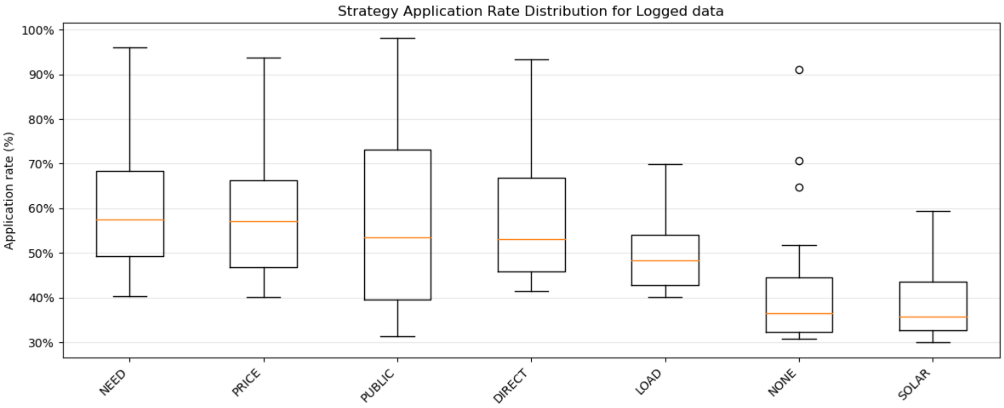


Figure 4.5: Distribution of strategy application rates for logged charging behaviour. Only individuals who exceeded the minimum application thresholds for the respective charging strategies are included. The figure therefore illustrates variation in behavioural consistency among users of each strategy; overall strategy prevalence is reported separately. The box indicates the interquartile range (25th–75th percentile), with the orange line marking the mean application rate. The whiskers extend to the full observed range within the sample, and a longer whisker indicates greater variability. Circles denote statistical outliers, representing users who applied the strategy at exceptionally high rates. Abbreviations are consistent with the definition made in Figure 4.1.

4.3.3 Combination patterns in logged data

The three most common strategy combinations in the logged dataset are presented in Table 4.6. The results show a clear dominance of the price-aware–need-based pattern, reported by 59% of participants, making it by far the most prevalent combination. The remaining combinations occur at substantially lower frequencies: the opportunistic-direct–none combination accounts for 11% of cases, while the solar-oriented–need-based pattern represents 7%. Although combinations involving three or more strategies do occur, they are comparatively rare and therefore not included among the primary patterns reported here. Given the sharp decline in prevalence beyond the dominant combination, these low-frequency patterns should be interpreted descriptively and used primarily to inform hypothesis generation rather than to draw strong behavioural conclusions.

Table 4.6: Strategy combinations indicated in the behavioural data. Abbreviations are consistent with the definition made in Figure 4.1.

Strategy combination	Occurence [%]
PRICE, NEED	59
DIRECT, NONE	11
SOLAR, NEED	7

4.4 Alignment between surveys and behaviour

This section analyses the alignment between self-reported strategies and observed charging behaviour. Each of the surveys are compared with the logged data separately, as this allows for analysis across a bigger population while still offering important insight. Comparisons include user-level alignment, strategy-level alignment, and improvement between surveys and logged data.

4.4.1 User-level alignment

Figure 4.6 illustrates the extent to which self-reported charging strategies from Survey A align with actual charging behaviour observed in the logged data. As shown in Figure 4.6, 22% of participants exhibit charging behaviour that fully corresponds to their self-reported strategies, indicating identical strategy sets across the survey responses and the logged data. Further, 45% display partial agreement, which by definition applies to participants reporting multiple strategies and indicates that at least one of the reported strategies is also reflected in the observed charging behaviour. The remaining 33% show no agreement, corresponding to a complete mismatch between stated strategies and observed behaviour. These results reveal a substantial degree of misalignment between reported charging intentions and actual behaviour, despite a majority of participants exhibiting some level of correspondence.

For Survey B, total agreement increases modestly to 26%, while partial agreement decreases slightly to 43%. The share of participants exhibiting no agreement is reduced marginally to 31%. Although these shifts suggest a small movement towards improved alignment, the overall distribution of agreement categories remains largely similar to that observed for Survey A. This indicates that changes between surveys are modest at the aggregate level, motivating a closer examination of individual-level improvements and deteriorations in alignment. It should be noted that the alignment outcomes reflect both user behaviour and the applied strategy classification rules; the latter are specified in Appendix A.2.

4.4.2 Strategy-level alignment

Strategy-level mismatch is presented in Figure 4.7 and illustrates the ways in which survey responses and logged data aligns or diverge. Across both surveys, most strategies exhibit neutral alignment. This can partly be explained by the relatively high share of participants who display total or partial agreement between reported and

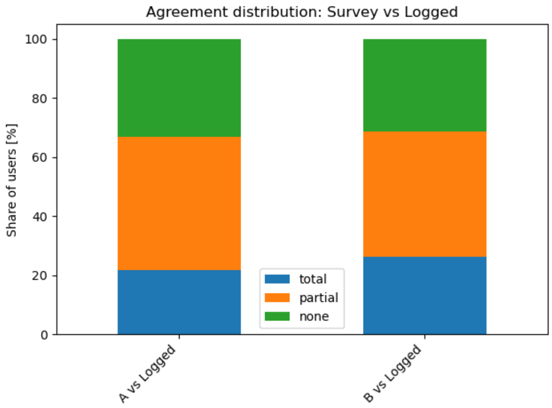


Figure 4.6: Distribution of agreement categories for comparisons between logged data and Survey A and Survey B. Total agreement indicates that the set of charging strategies reported by a participant exactly matches the set detected in the corresponding logged data. Partial agreement indicates that at least one charging strategy overlaps between the survey response and logged behaviour. No agreement indicates that there is no overlap between reported strategies and those identified in the logged data.

observed charging behaviour, amounting to approximately 70% as seen in Figure 4.6. When a participant's reported and observed strategies overlap, the corresponding strategy indicators coincide, which results in neutral alignment at the strategy level.

Despite this, substantial over-reporting is observed for the need-based and price-aware strategies. This indicates that these strategies are frequently reported even when their corresponding indicators are not consistently present in the logged data. This pattern is evident in both surveys and is slightly less pronounced in Survey B, suggesting a modest increase in reported-observed alignment over time for these two strategies.

At the same time, the need-based strategy also emerges as the most under-reported strategy, but slightly less so in Survey B. This indicates that charging behaviour consistent with the need-based indicator occurs for a considerable share of participants who do not explicitly report this strategy. The coexistence of both over- and under-reporting for the same strategy points to substantial variation in how participants interpret and enact the need-based concept.

Overall, the two surveys exhibit highly similar mismatch patterns, with only minor shifts in magnitude. This consistency suggests that discrepancies between reported strategies and observed behaviour are not driven by transient reporting noise, but instead reflect stable differences in how participants map abstract strategy labels onto their actual charging behaviour.

4.4.3 Improvement from A to B

This analysis compares responses from Survey A, Survey B, and the logged charging data for participants with complete observations across all three sources. This

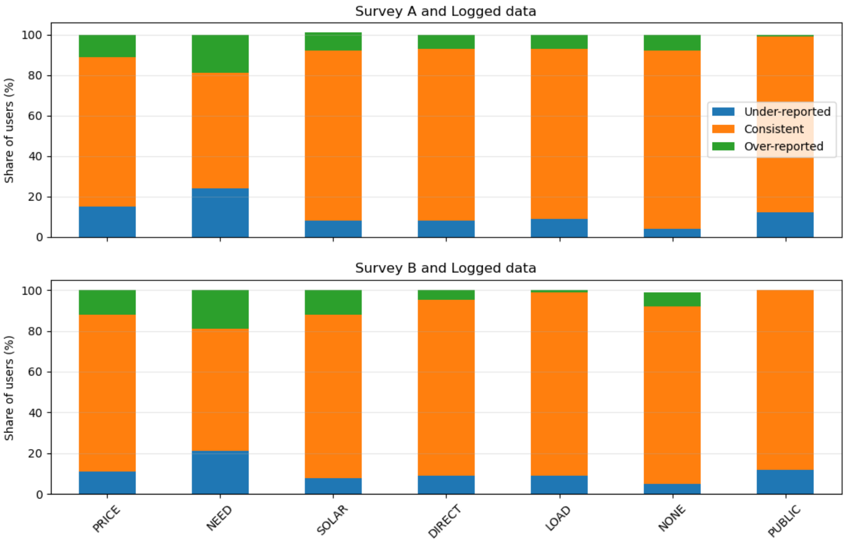


Figure 4.7: Strategy-level mismatch between self-reported charging strategies and observed charging behaviour for Survey A (top) and Survey B (bottom). For each strategy, the distribution shows the share of user exhibiting under-reporting (blue), neutral alignment (orange), or over-reporting (green) relative to the corresponding behavioural indicator derived from logged data. Abbreviations are consistent with the definition made in Figure 4.1.

means that the participant must have responded to both surveys and fulfilled the logging requirements. Restricting the sample to this common subset enables within-participant comparisons of reported charging strategies at both survey occasions and their corresponding observed behaviour. Agreement with logged data is evaluated using the predefined agreement categories, where total, partial, and no agreement are assigned scores of 2, 1, and 0, respectively. Improvement is subsequently quantified as the difference between Survey B and Survey A scores ($\text{Score}_B - \text{Score}_A$), allowing changes in alignment with observed behaviour to be assessed across surveys.

Aggregated improvement scores for Survey A and Survey B amount to 249 and 259, respectively, indicating a slightly higher overall level of alignment in Survey B relative to logged data. The absolute difference corresponds to a modest increase in user-level agreement and should be interpreted with caution given the discrete nature of the agreement scores.

As shown in Table 4.7, the distribution of individual improvement scores largely mirrors the aggregate-level alignment observed in Figure 4.6. The majority of participants (73%) exhibit no change in agreement with logged data between surveys. A total of 16% of participants show improved alignment, primarily driven by small positive score changes, while 11% exhibit decreased alignment. The resulting net increase in the aggregated improvement score reflects that improvements are more common than deteriorations, although most participants remain unchanged.

Table 4.7: Distribution of improvement scores in user-level agreement between surveys A and B relative to logged charging behaviour. Positive values indicate improved alignment, negative values indicate reduced alignment, and zero indicates no change.

Improvement score	
Score	Share [%]
2	4
1	12
0	73
-1	7
-2	4

4.5 Summary of key findings

- Reported strategy preferences in both surveys are dominated by need-based (around 40%) and price-aware charging (around 30%), while all other strategies occur at substantially lower frequencies (below 10%).
- A limited number of strategy combinations account for the majority of multi-strategy responses, with the need-based–price-aware combination being the most prevalent in both surveys (27% in Survey A and 40% in Survey B).
- Self-reported charging strategies exhibit moderate stability between surveys, with most participants showing total or partial agreement (78%), while a non-trivial share report completely different strategy sets (22%).
- Logged charging behaviour is concentrated, with need-based and price-aware behaviour dominating observed strategies, accounting for 39% and 25% of users, respectively.
- Consistency in application rates varies across charging strategies. Off-home, need-based, opportunistic-direct and price-aware charging exhibit wide spread, whereas solar-oriented, household load-aware and none charging show more tightly clustered application rates.
- Alignment between reported charging strategies and observed behaviour is limited across both surveys. Approximately 25% of participants achieve total agreement, while partial agreement is observed for around 45% of users and roughly 30% exhibit no agreement.
- Strategy-level mismatch exhibits consistent patterns across surveys. Need-based and price-aware strategies are frequently over-reported relative to observed behaviour, while need-based charging behaviour is also commonly observed among participants who do not explicitly report it as a strategy.
- Changes in survey–behaviour alignment from Survey A to Survey B are modest, with most participants exhibiting no change and small improvements slightly outnumbering deteriorations.

5

Discussion

5.1 Interpretation of the findings

The dominance of need-based and price-aware charging strategies in both self-reported preferences and observed charging behaviour suggests that EV users tend to gravitate towards strategies that are simple to apply and aligned with clear, prominent incentives. Both strategies can be implemented with relatively low cognitive effort and do not require continuous monitoring or complex planning, which may contribute to their widespread adoption.

For the price-aware strategy, the incentive structure is explicit: charging during periods of lower electricity prices directly reduces charging costs. Given that a substantial share of participants are exposed to variable or hourly electricity pricing, it is reasonable to expect that many users prefer to align charging with cheaper price periods, independent of more abstract considerations such as system-level optimisation.

The motivations underlying the need-based strategy are more heterogeneous. Postponing charging until the battery state of charge is low may reflect practical considerations such as predictable driving patterns, sufficient battery capacity, or access to multiple vehicles within the household. These combined factors help explain why need-based charging emerges as a dominant strategy despite the absence of an immediate financial incentive.

The observed distribution of combination drift between Survey A and Survey B suggests that self-reported charging strategies are generally stable over time. Nearly half of participants report identical strategy combinations across both surveys, indicating a strong persistence in how users conceptualise and describe their charging behaviour.

At the same time, a substantial share of participants exhibits small strategy drift, typically involving the addition or removal of a single strategy. This pattern points towards incremental adjustments rather than fundamental changes in charging behaviour or self-perception. Such shifts may reflect increased awareness of additional charging considerations, minor behavioural adaptations, or changes in how respondents interpret survey statements over time, rather than a complete reorientation of charging practices.

Moderate and large strategy drift are comparatively uncommon. Only a small fraction of participants display substantial changes in their reported strategy combinations, indicating that pronounced redefinitions of charging strategy are exceptional within the study population. Overall, the results support the interpretation that self-reported charging strategies remain relatively robust across survey waves.

For participants expressing multiple charging strategies, limited total agreement between self-reported strategies and logged behaviour is not unexpected. When users identify with more than one strategy, these strategies are unlikely to be applied uniformly across all charging events. As a result, an exact correspondence between reported strategy combinations and observed behaviour is improbable, even when the reported strategies are broadly reflected in practice.

This misalignment is particularly evident for strategy combinations that involve contextual or episodic components. For example, combinations that include solar-oriented charging are inherently constrained by external factors. Solar-oriented charging is seasonally dependent and limited to daylight hours, which restricts its consistent expression over time, especially during winter months. Consequently, a participant may meaningfully identify with a solar-oriented strategy while only expressing it intermittently in logged charging behaviour.

In comparisons between survey responses and logged data, total agreement is therefore observed for only a minority of participants. However, a substantially larger share exhibits partial agreement, indicating that at least one self-reported strategy is reflected in observed behaviour. This pattern suggests that partial agreement captures meaningful alignment, particularly for users with multi-strategy charging profiles. Notably, approximately 20% of participants completely changed their charging strategy across the two surveys, which could partly explain a third of the users not aligning at all with their corresponding logged data.

At the strategy level, mismatch reveals substantial heterogeneity in how individuals translate stated charging strategies into observed behaviour. This variation arises between individuals, rather than within individuals over time, as mismatch is calculated at the participant level using aggregated behavioural indicators.

The need-based strategy illustrates this heterogeneity particularly clearly. Participants classified under the need-based strategy display both positive and negative mismatch outcomes. This bidirectional pattern reflects the flexible and context-dependent nature of the need-based concept. For example, two participants may both identify as need-based chargers, while one consistently initiates charging at low state-of-charge due to long daily commutes, and the other charges earlier to maintain a safety margin. Despite identical self-reports, these behaviours result in opposite mismatch outcomes when evaluated against a common behavioural threshold.

This interpretation is supported by the broad distribution of strategy application rates observed for the need-based strategy, which indicates substantial between-user variation rather than systematic bias in self-reporting. In contrast, strategies anchored to more explicit external signals, such as price-aware charging, exhibit more concentrated mismatch patterns, reflecting narrower and more uniform behavioural interpretations across participants.

The modest improvement in alignment from Survey A to Survey B further supports the interpretation that self-reported charging strategies are temporally stable. Although Survey B is administered after additional charging experience, the aggregate increase in agreement with logged behaviour remains limited, indicating that most participants do not substantially recalibrate their stated strategies over time.

For the distribution of individual improvement scores, the dominance of zero change in agreement reinforces this pattern. Most participants maintain the same level of alignment across both survey waves, while improvements and deteriorations are observed for a smaller subset. Positive changes slightly outnumber negative ones, resulting in a net improvement in alignment.

Given that the improvement metric is limited to a narrow range of ordered categories, the magnitude of observed changes should be interpreted cautiously. Within these constraints, even small shifts reflect meaningful adjustments at the individual level. Overall, the findings indicate that experience and repeated reflection may refine self-reported charging strategies for some users, while persistence remains the dominant pattern.

5.2 Methodological considerations

The definition of charging strategies and the associated filtering of charging events represent important methodological choices that influence the resulting alignment and mismatch patterns. While the strategy definitions applied in this study enable systematic classification of charging behaviour, several aspects could be refined in future work to improve specificity and interpretability.

The need-based strategy is currently defined using a relatively permissive SoC threshold, where charging initiated below 50% SoC is considered indicative of need-based behaviour. While this captures a broad range of charging events, it also introduces heterogeneity, as remaining driving range at a given SoC varies substantially with battery size and vehicle efficiency. Consequently, a fixed SoC threshold may represent different levels of actual charging need across users. The definition could therefore be refined by incorporating vehicle-specific characteristics or by relating SoC thresholds to typical driving patterns, which would allow need-based behaviour to be defined more consistently across participants.

The solar-oriented strategy is implemented as a proxy for PV production based on temporal and irradiance-related conditions. However, the current implementation does not restrict the filter to participants who explicitly report owning solar panels. Although mismatch results suggest that under-reporting of the solar-oriented strategy is limited (indicating that the strategy rarely occurs in logged data without being reported) the inclusion of an ownership requirement would nonetheless improve conceptual consistency. More substantially, access to household-level solar production data along with energy storage data would allow direct identification of solar-driven charging behaviour and significantly strengthen the strategy definition.

Similarly, the household load-aware strategy is constructed as a proxy for real-world household load patterns, using predefined time windows to represent periods of lower expected load. While this approach captures general demand trends, the choice and number of low-load windows can influence overlap with other strategies, particularly price-aware charging. Although such overlap is accepted within the scope of this study, future work could explore alternative or more granular representations of household demand to better distinguish load-oriented behaviour from other time-dependent strategies.

Finally, the selection of application rate thresholds plays a central role in determining strategy alignment outcomes. In this study, thresholds are defined on a strategy-specific basis rather than using a single common threshold across all strategies. This approach accommodates strategies that are inherently limited in temporal availability, such as solar-oriented charging, but also introduces subjectivity in threshold placement. As thresholds are derived from empirical distributions subject to minimum requirements, their exact positioning cannot be considered definitive. Future studies could explore sensitivity analyses or adaptive thresholding approaches to assess the robustness of alignment results to alternative threshold definitions.

Logged charging data are used as a reference for comparison, but it does not fully capture users' intentions or reasoning. Survey responses describe how users generally conceptualise their charging behaviour, while logged data reflect what occurred in individual charging situations. As a result, differences between reported strategies and observed behaviour do not necessarily indicate incorrect reporting. For example, a participant may report following a need-based charging strategy but still initiate charging at relatively high SoC levels, such as when anticipating a long trip or maintaining a safety margin. In this case, the mismatch reflects differences in how the strategy is operationalised rather than a discrepancy between intention and behaviour.

Survey design and self-reporting represent inherent constraints of this study, as both surveys were designed independently of the present analysis. Consequently, charging strategies are reported based on respondents' subjective interpretations and may reflect general intentions rather than specific charging decisions. Differences between survey responses and logged behaviour may therefore partly stem from how strategies are framed and understood in the surveys, rather than from inconsistencies in behaviour.

5.3 Future work

Future work could build on the findings of this study by improving the representation of charging behaviour and its underlying drivers. Access to household-level energy demand, PV production and storage data would allow proxy-based strategy definitions to be replaced with more direct behavioural indicators. In addition, the behavioural strategy filters could be further refined and validated using richer contextual and infrastructural information. Future work could also entail exploring different charging trends across different subgroups such as users living in houses or apartments, urban or rural areas,gender and age, or multiple-car households. Information of typical use for these subgroups could offer valuable insight for grid-planning, policy making and infrastructure decisions. Finally, extending the current framework towards probabilistic or mixed-strategy representations could better capture the coexistence and varying intensity of multiple charging strategies at the individual level.

6

Conclusion

6.1 Summary and contributions

This thesis assesses the extent to which private EV owners apply different charging strategies and examines discrepancies between self-reported strategies and observed charging behaviour derived from logged data.

RQ1 examined which charging strategies are reported by EV owners based on the survey responses. Results show that self-reported charging strategies are dominated by need-based and price-aware charging, reported by approximately 40% and 30% of participants, respectively, often in combination. All other strategies occur at substantially lower frequencies, typically below 10%. A limited number of strategy combinations account for most multi-strategy responses, with the need-based–price-aware combination being the most prevalent in both surveys.

RQ2 assessed the alignment between self-reported charging strategies and observed charging behaviour. Alignment between reported charging strategies and observed behaviour is limited. Across both surveys, total agreement is observed for around 25% of participants, partial agreement for approximately 45%, and no agreement for about 30%. Observed charging behaviour is concentrated, with need-based and price-aware behaviour accounting for approximately 39% and 25% of users, respectively.

Overall, the results indicate that private EV owners consistently report a small set of dominant charging strategies, while alignment between these self-reported strategies and observed charging behaviour remains limited.

6.2 Implications and final remarks

This thesis shows that discrepancies between self-reported charging strategies and observed charging behaviour cannot be interpreted solely as inaccuracies in self-reporting. While logged charging data provide detailed records of charging outcomes, they do not capture the contextual factors or considerations that influence individual charging events. As a result, observed mismatches may reflect unobserved constraints, anticipatory behaviour, or situational factors rather than inconsistency or error.

The findings therefore highlight both the value and the limitations of combining survey-based and logged charging data. Self-reported strategies provide insight into how users conceptualise and reason about their charging practices, while logged data reveal how charging unfolds under real-world conditions. Robust interpretation of charging strategies requires acknowledging the partial and complementary nature of these data sources, rather than treating either as a definitive reference.

In this sense, the contribution of the thesis lies in advancing the understanding of how reported charging strategies relate to observed charging patterns. While the results should not be interpreted as a direct basis for policy-making or grid planning, they provide indicative insights that may inform future research and, with further validation and contextualisation, support decision-making processes for actors such as grid operators, aggregators, and researchers.

Bibliography

Chatzouli, M., Weckesser, T., Yousefi, G., Thingvad, M., Calearo, L., Marinelli, M., & Ziras, C. (2025). Which electric vehicle users are flexible and price responsive? uncovering user types in denmark. *Energy Research & Social Science*, *127*, 104240. https://doi.org/https://doi.org/10.1016/j.erss.2025.104240

European Environment Agency. (2024). New registrations of electric vehicles [Accessed: 6 January 2026].

European Parliament. (2019). Co2 emissions from cars: Facts and figures (infographics) [Accessed: 6 January 2026].

Geotab Inc. (2025). Go device logging [Accessed: 2026-01-04]. https://developers.geotab.com/myGeotab/guides/goDeviceLogging/index.html

Huang, P., & Ma, Z. (2024). Unveiling electric vehicle (ev) charging patterns and their transformative role in electricity balancing and delivery: Insights from real-world data in sweden. *Renewable Energy*, *236*, 121511. https://doi.org/https://doi.org/10.1016/j.renene.2024.121511

International Energy Agency. (2025). *Global ev outlook 2025: Executive summary* (Accessed: 6 January 2026). International Energy Agency. https://www.iea.org/reports/global-ev-outlook-2025/executive-summary

International Renewable Energy Agency. (2019, May). *Innovation outlook: Smart charging for electric vehicles* (Accessed: 16 Jan 2026). International Renewable Energy Agency (IRENA). Abu Dhabi. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/May/IRENA_Innovation_Outlook_EV_smart_charging_2019.pdf

Jaramillo, P., Kahn Ribeiro, S., Newman, P., Dhar, S., Diemuodeke, O., Kajino, T., Lee, D., Nugroho, S., Ou, X., Hammer Strømman, A., & Whitehead, J. (2022). Transport. In P. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *Climate change 2022: Mitigation of climate change. contribution of working group iii to the sixth assessment report of the intergovernmental panel on climate change.* Cambridge University Press. https://doi.org/10.1017/9781009157926.012

Kobayashi, Y., Taljegard, M., & Johnsson, F. (2025). Assessment of real-world driving patterns for electric vehicles: An on-board measurements study from sweden. *Applied Energy*, *401*, 126608. https://doi.org/https://doi.org/10.1016/j.apenergy.2025.126608

Liao, Y., Tozluoğlu, Ç., Sprei, F., Yeh, S., & Dhamal, S. (2023). Impacts of charging behavior on bev charging infrastructure needs and energy use. *Transportation Research Part D: Transport and Environment*, *116*, 103645. https://doi.org/https://doi.org/10.1016/j.trd.2023.103645

Nord Pool. (2025). Nord pool group, Price Index - Day Ahead Market for SE1,SE2,SE3 SE4 [Accessed: 2025-11-04].

Power Circle. (2022). *Smart laddning av elfordon – en nyckel till ett hållbart elsystem.* Retrieved August 3, 2025, from https://powercircle.org/smartladdning.pdf

SCB. (2025a). Database of household residences (hushållens boende) [Accessed: 2026-01-04]. https://www.scb.se/hitta-statistik/statistik-efter-amne/boende-bebyggelse-och-mark/bostader-och-boende/hushallens-boende/

SCB. (2025b). Geographical database (geografidatabasen) [Accessed: 2026-01-04]. https://www.scb.se/vara-tjanster/bestall-data-och-statistik/register/geografidatabasen/

SCB. (2025c). Register of the total population (rtb) [Accessed: 2026-01-04]. https://www.scb.se/vara-tjanster/bestall-data-och-statistik/register/registret-over-totalbefolkningen-rtb/

SCB. (2025d). Vehicle register (fordonsregistret) [Accessed: 2026-01-04]. https://www.scb.se/vara-tjanster/bestall-data-och-statistik/register/fordonsregistret/

Shariatzadeh, M., Lopes, M. A., & Henggeler Antunes, C. (2025). Electric vehicle users' charging behavior: A review of influential factors, methods and modeling approaches. *Applied Energy*, *396*, 126167. https://doi.org/https://doi.org/10.1016/j.apenergy.2025.126167

Sørensen, Å., Sartori, I., Lindberg, K., & Andresen, I. (2023). A method for generating complete ev charging datasets and analysis of residential charging behaviour in a large norwegian case study. *Sustainable Energy, Grids and Networks*, *36*, 101195. https://doi.org/https://doi.org/10.1016/j.segan.2023.101195

Swedish Meteorological and Hydrological Institute (SMHI). (2025). Strång – global irradiance data [Accessed: 2025-02-04].

Trafikanalys. (2024). *Korttidsprognoser för vägfordonsflottan 2025–2028.* Trafikanalys. https://www.trafa.se/vagtrafik/korttidsprognoser-for-vagfordonsflottan-2025-15418/

United Nations Framework Convention on Climate Change. (2015). Paris agreement [Adopted 12 December 2015, entered into force 4 November 2016].

Weekx, S., Van den bergh, O., Tal, G., & Vanhaverbeke, L. (2025). Ev charging habits and their impact on public charging infrastructure usage. *Transportation Research Part D: Transport and Environment*, *143*, 104730. https://doi.org/https://doi.org/10.1016/j.trd.2025.104730

Zatsarnaja, J., Mehdizadeh, M., Reiter, K., Nayum, A., & Nordfjærn, T. (2025). Charging patterns and motives of electric vehicle drivers: Insights from norway. *Travel Behaviour and Society*, *41*, 101094. https://doi.org/https://doi.org/10.1016/j.tbs.2025.101094

Ziras, C., Thingvad, M., Fog, T., Yousefi, G., & Weckesser, T. (2024). An empirical analysis of electric vehicle charging behavior based on real danish residential charging data. *Electric Power Systems Research*, *234*, 110556. https://doi.org/https://doi.org/10.1016/j.epsr.2024.110556

A

Appendix A

A.1 Codebook rules

This section documents the complete set of rules of the codebook used in the analysis. Survey response options are mapped to rule identifiers representing charging strategies. Each rule identifier is unique, and identical strategies across surveys are mapped consistently.

In cases where the survey wording does not map directly to a single charging strategy, the mapping is based on the dominant operational characteristic implied by the response. This ensures consistent classification across surveys and versions.

Table A.1: Codebook mapping between survey response options and charging strategies

Survey	src question	src option	strategy	version	rule id
A	q24	Laddar elbilen så fort den parkeras vid bostaden oavsett laddnivå på batteriet	DIRECT	v3.0	`ANCH_A_001@v3.0`
A	q24	Laddar elbilen så fort den parkeras vid bostaden om det finns en ledig laddare	NONE	v3.0	`ANCH_A_005@v3.0`
A	q24	Laddar elbilen när inte så mycket annan el i hushållet används för att undvika att säkringarna går	LOAD	v1.0	`ANCH_A_003@v1.0`
A	q24	Laddar elbilen så fort den parkeras vid bostaden om batterinivån är låg	NEED	v1.0	`ANCH_A_002@v1.0`
A	q24	Det finns ingen direkt laddningsstrategi	NONE	v1.0	`ANCH_A_007@v1.0`
A	q24	Laddar elbilen mestadels när elpriset är lågt	PRICE	v1.0	`ANCH_A_004@v1.0`
A	q24	Laddar elbilen när mina solceller producerar el	SOLAR	v3.0	`ANCH_A_006@v3.0`
A	q24	Other	UNIQUE	v1.0	`ANCH_A_008@v1.0`
B	q23	Laddar elbilen så fort den parkeras vid bostaden oavsett laddnivå på batteriet	DIRECT	v3.0	`ANCH_B_001@v3.0`
B	q23	Laddar elbilen så fort den parkeras vid bostaden om det finns en ledig laddare	NONE	v3.0	`ANCH_B_005@v3.0`
B	q23	Laddar elbilen så fort den parkeras vid bostaden om batterinivån är låg	NEED	v1.0	`ANCH_B_002@v1.0`
B	q23	Det finns ingen direkt strategi	NONE	v1.0	`ANCH_B_007@v1.0`
B	q23	Låter mitt elhandelsbolag optimera när min laddning ska ske (t.ex. med hjälp av tibber)	PRICE	v1.0	`ANCH_B_003@v1.0`

Continued on next page

Survey	src question	src option	strategy	version	rule id
B	q23	Laddar elbilen mestadels när elpriset är billigt	PRICE	v1.0	`ANCH_B_004@v1.0`
B	q23	Laddar elbilen i första hand när mina solceller producerar el	SOLAR	v3.0	`ANCH_B_006@v3.0`
B	q23	Other	UNIQUE	v1.0	`ANCH_B_008@v1.0`
P	q21	Laddar elbilen så fort den parkeras vid bostaden oavsett laddnivå på batteriet	DIRECT	v3.0	`ANCH_P_001@v3.0`
P	q21	Laddar elbilen så fort den parkeras vid bostaden om batterinivån är låg	NEED	v1.1	`ANCH_P_002@v1.1`
P	q21	Laddar elbilen när inte så mycket annan el i hushållet används för att undvika att säkringarna går	LOAD	v1.1	`ANCH_P_003@v1.1`
P	q21	Laddar elbilen mestadels när elpriset är billigt	PRICE	v1.1	`ANCH_P_004@v1.1`
P	q21	Laddar elbilen så fort den parkeras vid bostaden om det finns en ledig laddare	NONE	v3.0	`ANCH_P_005@v3.0`
P	q21	Det finns ingen direkt strategi	NONE	v1.1	`ANCH_P_006@v1.1`
P	q21	Other	UNIQUE	v1.1	`ANCH_P_007@v1.1`

A.2 Strategy filters and classification rules

This section provides a detailed description of the strategy filter definitions and the specific criteria used during classification. It also outlines the procedure used to define thresholds for the minimum application rate.

A.2.1 Strategy specific filter criteria

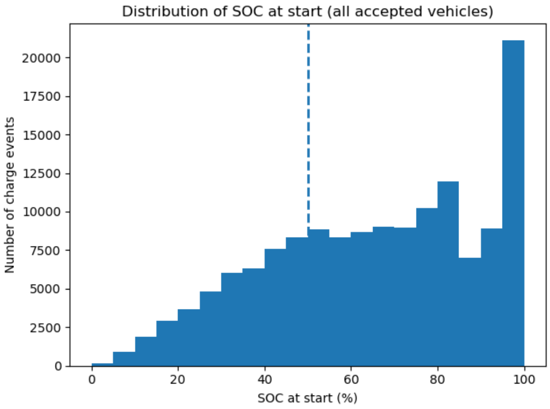


Figure A.1: SOC at start for all charging events for all accepted vehicles. The dashed line is placed at 50%

The need-based strategy applies one criterion: charging is initiated at a relatively low SOC. To determine an appropriate threshold, the starting SOC for all charging events across all EVs that passed initial preprocessing was examined. As shown in Figure A.1, no clear empirical breakpoint exists at which users consistently initiate charging. However, from a conceptual perspective, a charging event initiated at a battery level below 50% can reasonably be interpreted as necessity-driven, whereas charging initiated above 50% SOC is typically not associated with an immediate need and can therefore be postponed. In conclusion, a threshold of 50% SOC at the start of charging is adopted as the feasibility condition for the need-based strategy. The solar-oriented strategy also applies one criterion: charging must align with hours where solar production is feasible. Neither power-production data or information about installation size is available. As a plausibility check, PV output is assumed to scale approximately linearly with irradiance at low power levels. A simple back-of-envelope approximation is given by

$$P_{\mathrm{PV,AC}} \approx P_{\mathrm{STC}} \cdot \frac{G}{1000} \cdot \eta_{\mathrm{sys}}, \tag{A.1}$$

where P_{STC} is the installed PV capacity at standard test conditions, G is the global horizontal irradiance (GHI), and η_{sys} represents lumped system losses, including inverter and wiring losses (here assumed to be approximately 0.8).
For $G = 150\ \mathrm{W/m^2}$, this yields

$$P_{\mathrm{PV,AC}} \approx 0.12\, P_{\mathrm{STC}}, \tag{A.2}$$

corresponding to very low but technically non-zero available PV power. This order of magnitude is consistent with slow EV charging and therefore motivates the use of 150 W/m^2 as a generous but plausible lower bound for solar-feasible EV charging conditions. Below this irradiance level, PV output is assumed insufficient to sustain meaningful charging due to inverter, charger, and vehicle constraints.

For the price-aware strategy, charging events are classified as price-aligned when they occur during hours in which the electricity spot price is below the daily average. Prices are evaluated separately for each Swedish bidding zone (SE1–SE4), ensuring that the classification reflects the local electricity market conditions faced by each user. Using the daily average as a reference provides a simple and transparent benchmark for identifying relatively low-price periods without relying on absolute price levels.

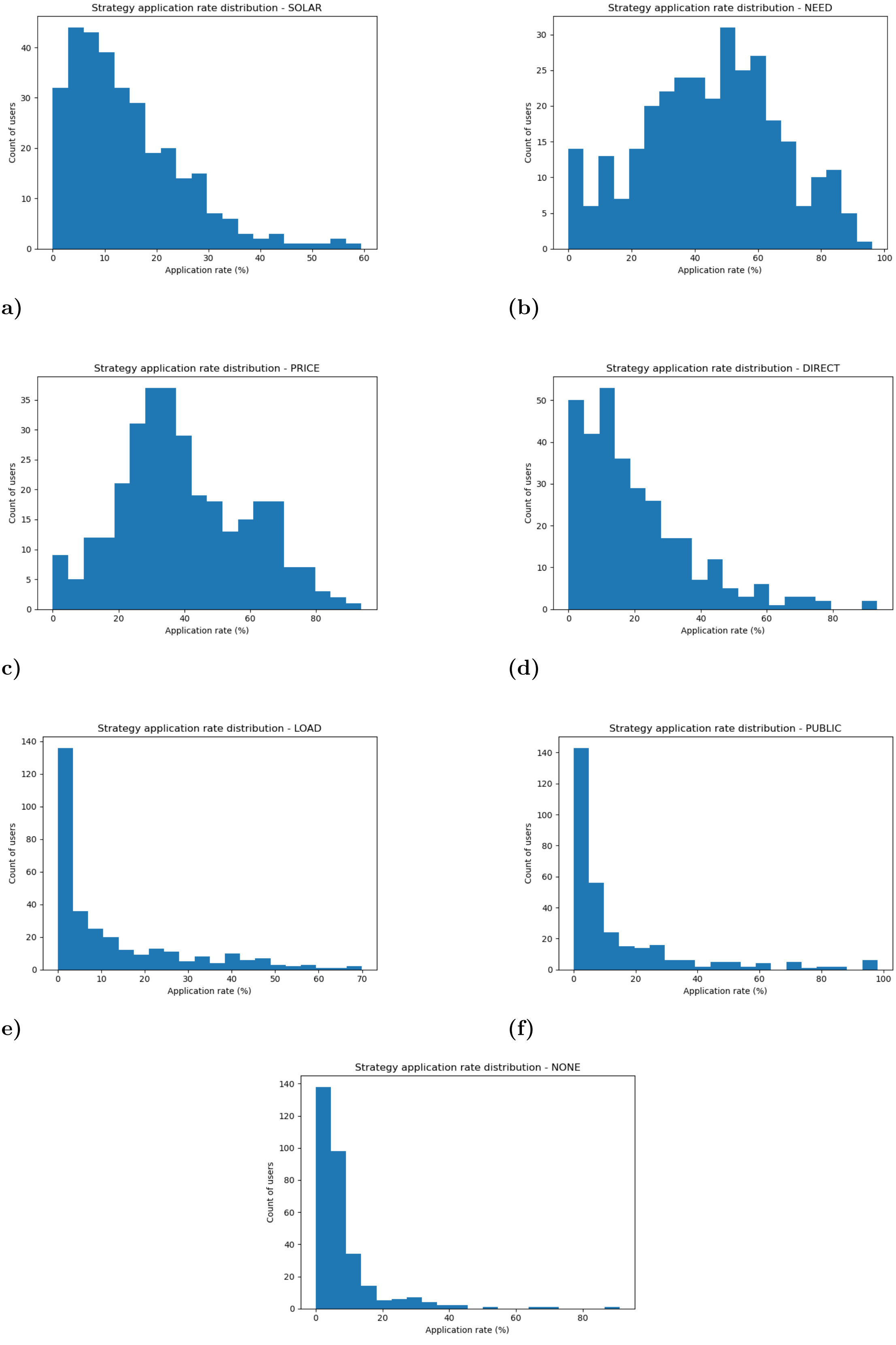
The opportunistic direct strategy is defined by two criteria: charging is initiated shortly after arrival and occurs at a relatively high SOC. To ensure consistency with the need-based strategy, the same SOC threshold is applied, but with the opposite condition; charging events are classified as opportunistic-direct when the starting SOC is at or above 50%. In addition, a maximum delay of 10 minutes between arrival and charging initiation is imposed, ensuring that charging is initiated immediately rather than deliberately postponed.

The household load-aware strategy is implemented using a fixed charging time window as a proxy for household load conditions. As detailed household load profiles are not available, charging events occurring between 22:00 and 05:00 are classified as load-aligned, reflecting periods that are generally associated with lower household electricity demand. While this time window may overlap with other considerations such as low electricity prices, it serves as a practical approximation of household load conditions given the available data.

The off-home charging strategy is defined by a single spatial criterion: charging occurs outside the home location. A charging event is classified as off-home when the charging location is identified as either “Work” or “Other”. This strategy captures charging behaviour that relies on external charging opportunities rather than residential infrastructure.

The none strategy is defined at the event level as the complement of all other strategies. A charging event is classified as non-optimised if none of the strategy-specific conditions are satisfied during that event. This category therefore represents periods of charging that do not align with any of the defined strategies.

A.2.2 Setting minimum application rates



(a) **(b)** **(c)** **(d)** **(e)** **(f)** **(g)**

Figure A.2: Distribution of application rates for each strategy. The y-axis denotes user counts.

To determine the minimum application rate for each strategy, the overall distribution of application rates across users is examined. While the minimum application rate is informed by both the empirical distributions and the conceptual characteristics of the strategies, a common lower bound of 30% is applied across all strategies. Application rates below this level are interpreted as sporadic or incidental alignment with the strategy criteria rather than indicative of consistent charging behaviour. The strategy-specific distributions of application rates are shown in FigureA.2.

FigureA.2a shows that most users align with the solar-oriented strategy for only a small share of their total charging time, predominantly within the 0–20% range. This pattern reflects the episodic nature of the strategy, as solar generation is restricted to daylight hours and varies seasonally. Despite this, the minimum application rate for the solar-oriented strategy is set at 30%, meaning that nearly one-third of a user's charging time must coincide with periods of solar generation in order to be classified as applying the strategy.

For the need-based strategy (FigureA.2b), the distribution is more evenly spread, with most users exhibiting application rates between 25–70%. To distinguish a dominant behavioural tendency from occasional low-SOC charging, the minimum rate is set at 40%, meaning that at least 40% of total charging events must be initiated at low battery levels.

A similar distribution is observed for the price-aware strategy (FigureA.2c), with application rates centred around 20–65%. Consistent with the need-based strategy, a minimum application rate of 40% is applied to identify users for whom price responsiveness constitutes a predominant charging behaviour.

For the opportunistic-direct strategy (FigureA.2d), the distribution is strongly right-skewed, with most users aligning with the strategy for only 0–20% of their charging time. As with the solar-oriented strategy, a minimum application rate of 30% is applied to distinguish repeated strategic behaviour from incidental use. The same minimum-rate logic is applied to the remaining strategies—household load-aware, off-home, and non-optimised charging—as shown in FiguresA.2e–A.2g. For the household load-aware strategy, substantial overlap with other strategies limited the discriminative power of the initial minimum rate. The minimum application rate was therefore increased to 40% to ensure that the strategy reflects a dominant behavioural pattern rather than coincidental alignment.

B

Appendix B

B.1 Data quality requirements and exclusion outcomes

Based on Kobayashi et al. (2025), the following parameters were adopted: an average annual driving distance of 16 500 km, an average energy consumption of 0.156 $\text{kWh}\,\text{km}^{-1}$, and charging power levels of 3–4 kW and 9–10 kW.

A minimum of 90 days of logged data was required for inclusion in the analysis, this limit was set to ensure recurring charging patterns. A lower limit could have introduced random or sporadic charging behaviour while a higher limit would have significantly reduced the sample size. The 90 day requirement corresponds to a driven distance of

$$16\,500 \cdot \frac{90}{365} \approx 4\,068 \text{ km}. \tag{B.1}$$

The corresponding energy demand is given by

$$E = 4\,068 \cdot 0.156 \approx 634 \text{ kWh}. \tag{B.2}$$

Assuming constant charging power, the required charging time is bounded by

$$t_{\text{min}} = \frac{634}{10} \approx 63.4 \text{ h}, \tag{B.3}$$

and

$$t_{\text{max}} = \frac{634}{3} \approx 211.3 \text{ h}. \tag{B.4}$$

Expressed in minutes, this corresponds to approximately 3 804 and 12 678 minutes, respectively. For this analysis, an average charging power of 7 kW is assumed, resulting in a required charging time of approximately 5 400 minutes over 90 days. Table B.1 show the minimum data requirements for this analysis. The exclusion result is showed in Table B.2.

Table B.1: Summary of minimum data requirements for EVs to be included in analysis

Minimum Type	Limit	Reason
Logged days	90	Ensure habitual use
Logged charging minutes	5400	Ensure data availability

Table B.2: Exclusion results from basic preprocessing

Filtering step	Number of users	Excluded number of users
Baseline	384	0
Minimum logged days	369	15
Minimum logged time	328	41
Corresponding ID in surveys	314	14

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