Travel Behaviour and Society 41 (2025) 101094

Contents lists available at ScienceDirect

Travel Behaviour and Society

journal homepage: www.elsevier.com/locate/tbs

Charging patterns and motives of electric vehicle drivers: Insights from Norway

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ARTICLE INFO

Keywords:
Electric mobility
Electric vehicle drivers
Drivers' charging behavior
Sustainable charging

ABSTRACT

As the adoption of electric vehicles (EVs) grows, understanding charging behavior becomes important due to increasing charging demand and grid load. Based on a population-based survey with 1,005 Norwegian EV drivers, we uncover three classes of (revealed) charging behavior: daily convenient chargers, battery-exploiting seldom chargers, and occasional battery-friendly planners. The first class consists of EV drivers who typically use every opportunity to keep the battery level of their EV between 40 % and 100 % and charge mainly at home or work. The second class includes drivers who charge their EV 2–3 times per week or rarely, carry out charging according to their driving needs, wait until the battery level is low (<30 %), and charge at home or in public. By planning their charging needs, holding the battery at an optimal level of 30 %–80 %, conducting charging 4–5 times per week, and mostly at home, the third group reflects the most sustainable and battery-friendly behavior. Our findings revealed that EV drivers who are male, have longer EV driving experience, drive longer distances, are socially less persuadable, and do not seize the available potential to charge rarely, are more likely to be daily convenient chargers than battery-friendly chargers. Meanwhile, EV drivers with lower daily mileage, who perceive guidance from their charging apps as less helpful, find it easy to start charging at a low battery level and have a higher general risk propensity are more likely to be battery-exploiting seldom chargers than battery-friendly planners.

1. Introduction

The global shift towards sustainable transport has led to a rapid adoption of electric vehicles (EVs) in recent years. In 2023, the number of EV sales worldwide reached 14 million (International Energy Agency, 2024) compared to 2018 in which the number of EVs sold worldwide was only 2 million (Statista, 2024a). This represents a significant milestone in the transition away from traditional internal combustion engine vehicles. Nowadays the growth is largely driven by advancements in battery technology, government incentives, and growing consumer awareness of the environmental and economic benefits of EVs (International Energy Agency, 2024).

However, the successful integration of EVs into the transportation ecosystem hinges not only on their widespread adoption but also on the efficient management of EV drivers' charging behavior (Alaee et al., 2023). EV owners' decisions regarding when, where, and how to charge their vehicles can have profound implications for the stability and resilience of the electric grid (Hardman et al., 2018), as well as the overall user experience and adoption rates (Bühler et al., 2014). Understanding the factors that influence EV charging behavior is, therefore, important. Studies have shown that a complex interplay of individual, technological, and contextual factors can shape the charging habits and preferences of EV owners (e.g., Daina et al., 2017; Hardman et al., 2018). Factors such as socioeconomic status, environmental consciousness, range anxiety, charging infrastructure availability, and workplace policies can all contribute to the unique charging behaviors observed across different EV user groups (e.g., Khaleghikarahrodi & Macht, 2023; Liao et al., 2023; Sprei & Kempton, 2024). By examining these influential factors, researchers, industry and policymakers can develop targeted strategies and interventions to optimize EV charging

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https://doi.org/10.1016/j.tbs.2025.101094
Received 31 October 2024; Received in revised form 4 February 2025; Accepted 30 June 2025
Available online 4 July 2025

patterns regarding grid use and battery longevity.

Our study further contributes to this discussion by providing insights from a nationwide survey with N = 1,005 EV drivers in Norway. Thereby, we consider Battery Electric Vehicle (BEV) drivers only. As of 2023, Norway had the highest share of new EV registrations in Europe where EVs (including Plug-In Hybrid Vehicles – PHEVs) account for almost 95 % of new car sales (International Energy Agency, 2024). Moreover, with nearly 690,000 registered EVs (including PHEVs), their share among all registered private vehicles is around 23.87 % (Statistics Norway, 2024) compared to 4.8 % in Germany (Statista, 2024b). This renders the Norwegian EV market an intriguing avenue for studying revealed charging behavior because such a high adoption rate and long temporal presence of electric mobility allow the formation of different user profiles and charging patterns. Considering the complexity of the decision-making process in terms of EV charging, it is of great interest to understand how these differences in charging behavior can be systematically categorized and described. In addition, it is crucial to know the main influencing factors for charging pattern formation and how these differ, to target the diverse needs of EV drivers while successfully promoting sustainable charging behavior.

In our exploratory study, we first cluster EV drivers according to their charging frequency, main charging location, employed charging strategy, and battery level at the start and end of charging. Then we examine how the combination of variables describing socio-demographics (age, gender, settlement size), EV driving- and charging-related aspects (EV experience, daily mileage, charging guidance, charging process, flexibility in terms of charging frequency and battery level), and psychological background (technology openness, general risk propensity, ecological awareness, economic and social motives) can be associated with these charging patterns. Precisely, technology openness indicates drivers' acceptance to embrace new technologies and risk propensity explains the willingness to take risks in general life. Ecological awareness evaluates pro-environmental thinking and purchase motives showing how much cost-saving reasons and own social environment motivated drivers' EV purchase. Our findings could provide important ramifications for sustainable charging behavior with all its benefits for the environment, energy management, and battery health.

2. Literature review

2.1. Electric vehicle charging behavior styles

Researchers have explored archetypes or patterns of EV drivers' charging behavior to understand the variability of needs and their impact on charging infrastructure. Khaleghikarahrodi and Macht (2023) conducted a cluster analysis of EV charging behavior based on charged energy and frequency, identifying four types of EV drivers: convenient, gradual, anxious, and urgent. Nazari and Musílek (2024) identified four distinct user groups, each exhibiting unique charging behaviors, such as connection time and session duration. Afternoon users showed a significant demand for energy, with peak charging occurring in early afternoons. Huang et al. (2024) analyzed EV charging patterns, focusing on station distribution, volume, duration probability, and utilization efficiency. These studies highlight disparities in infrastructure availability and emphasize strategic planning to meet growing charging demands and to optimize network operations.

Helmus et al. (2020) and Wolbertus et al. (2018) explored the timing of charging, defining nine user types and five classes, respectively. Both studies concluded that showcasing only stereotypical behavior fails to capture the full range of behaviors. Morrisey et al. (2016) analyzed charging behavior regarding charging location, charged energy, charge duration, and charging mode. Authors identified that the majority of home charging is carried out in the evening, car parks are the most preferred charging location and fast charging is the most favored charging mode in public space.

Liao et al. (2023) conducted a nationwide simulation for future EV charging infrastructure scenarios in Sweden, categorizing EV drivers based on charging places, daily activities, and parking time. Aligned with mental models by Sprei and Kempton (2024), they distinguished between three charging strategies: liquid-fuel, plan-ahead, and event-triggered. Inexperienced EV drivers tended to charge when the battery level approached empty, while experienced ones usually charged when triggered by an event or opportunity.

Other researchers used a survey approach based on stated preference to gather data about the perception of charging. Based on drivers' charging strategies to cope with battery resources and risk propensity Hajhashemi et al. (2024) identified five distinct charging styles: cost-sensitive planners, cost-sensitive calculated, range seekers, flexibility seekers, and indifferent late adopters. Wang et al. (2021) revealed two classes of charging-decision-making patterns. These were service-concerned drivers who mainly focus on the service level of the facility, regardless of the charging costs. Others are pragmatic-concerned drivers who consider reality factors, such as charging fee and SOC, rather than satisfaction.

These studies acknowledge the heterogeneity in charging behavior and suggest the need for flexibility in charging choices, particularly regarding future developments in battery technology and estimating the load on the charging infrastructure. However, the mentioned works often include early EV adopters or potential EV drivers without prior experience, limiting the empirical inquiry to their stated preferences rather than revealed behavior. Additionally, the studies predominantly use a descriptive approach based on a few charging attributes. This hinders deeper investigation into the socio-demographic, contextual, and psychological factors that shape these charging patterns. Hence, we need to explore additional literature to better understand the variety and significance of these factors for charging behavior in general.

2.2. Factors influencing electric vehicle charging behavior

Current literature on potential precursors of EV charging behavior is mainly based on findings from field experiments and questionnaire studies. Several of these studies found that charging frequency can be positively influenced by higher mileage (Daina et al., 2015; Philipsen et al., 2018; Yang et al., 2016), more frequent driving (Philipsen et al., 2018), low charging costs (Yang et al., 2016), higher vehicle energy consumption (Yang et al., 2016), or smaller EV range (Daina et al., 2015; Helmus et al., 2020). The charging frequency increases when the EV driver charges according to habit (Daina et al., 2015; Philipsen et al., 2018), is a female driver (Thorhauge et al., 2024; Yang et al., 2016; Wang et al., 2021), has a younger age (Thorhauge et al., 2024; Daina et al., 2015; Yang et al., 2016), a higher education level (Daina et al., 2015; Yang et al., 2016), or lives in a bigger settlement (Pevec et al., 2020). Another essential factor characterizing charging behavior is the state of charge (SOC) at the charging start. Researchers found that higher age (Daina et al., 2015), longer distance to work (Daina et al., 2015), larger battery capacity (Helmus et al., 2020; Khaleghikarahrodi & Macht, 2024), higher general risk propensity (Hu et al., 2019; Philipsen et al., 2018), and need-based charging (Helmus et al., 2020; Philipsen et al., 2018) made EV drivers start charging at a lower battery level.

Furthermore, the preferred location of charging stations is also associated with several individual variables. Home charging has been highlighted as the most important and convenient charging location followed by work and public charging (Hardman et al., 2018; Hu et al., 2019; Neubauer & Wood, 2014). EV drivers favoring charging at home tend to be female and have a higher age (Guo et al., 2022; Lee et al., 2020), do not have workplace charging availability (Chakraborty et al., 2019; Lee et al., 2020), or an inexpensive charging alternative elsewhere (Chakraborty et al., 2019; Yang et al., 2016). In contrast, EV drivers charging at work can be described as individuals with higher education, and with less expensive or even free workplace charging availability

(Chakraborty et al., 2019; Lee et al., 2020). Typical workplace chargers avoid low SOC and prefer charging at every opportunity, with short and medium-duration chargings occurring in the morning until the afternoon, and longer durations postponed to the end of the day (Fieltsch et al., 2020). These EV drivers, who use public charging stations the most, are usually male (Lee et al., 2020), have lower EV range (Chakraborty et al., 2019), lower starting SOC (Hu et al., 2019), and no workplace charging availability (Chakraborty et al., 2019; Lee et al., 2020).

Moreover, rational EV use has been related to more practical driving experience (Franke et al., 2017; Rauh et al., 2020; Thorhauge et al., 2024) but also to more range-related knowledge and availability of in-vehicle information (Rauh et al., 2020; Yang et al., 2016). However, Liao et al. (2023) found that inexperienced EV drivers tend to charge only if necessary, and experienced ones according to their habits. Besides, Franke and Krems (2013) found in their study that a higher willingness to reduce their own cognitive and battery load for charging more often than necessary is associated with higher confidence in range estimates and range utilization.

2.3. Current study

The existing literature on EV drivers' charging behavior contains valuable insights but has several limitations that our study aims to address. Previous research has often focused on small-scale samples or included a mix of EV, PHEV, and ICE drivers (Daina et al., 2015; Franke et al., 2017; Hajhashemi et al., 2024; Pevec et al., 2020), which may not fully capture the nuances of charging behavior among a large, diverse population of EV drivers.

Some studies have relied solely on records of public charging stations (e.g., Khaleghikarahrodi & Macht, 2023; Morrissey et al., 2016). Others have used mathematical simulations (Liao et al., 2023; Neubauer & Wood, 2014), which, although useful, may not reflect the comprehensive and representative factors that shape the heterogeneity of human behavior. Additionally, many studies have been conducted in countries with lower EV adoption rates (e.g., Daina et al., 2017; Khaleghikarahrodi & Macht, 2023; Philipsen et al., 2018), limiting the ability to draw insights on revealed charging habits in more mature electric mobility markets.

Our study investigates the charging behavior of 1,005 EV drivers in Norway, a country with one of the highest EV adoption rates worldwide and a strongly favorable environment for electric mobility. By conducting a nationwide survey with a diverse sample of EV drivers, we aim to provide a more comprehensive understanding of the variety of charging behavior patterns and the underlying motivations. We cluster EV drivers in our sample according to the charging behavior indicators, such as charging frequency, charging place, charging strategy as well as SOC at the start and end of charging. The five indicators were chosen based on previous literature which employed them in different contexts and separate settings (Daina et al., 2015; Hu et al., 2019; Liao et al., 2023; Philipsen et al., 2018).

Moreover, past research lacks a unified association of socio-demographic, charging- and psychology-related factors with charging behavior. The examination of these variables in one model would not solely enable identification of the variety of charging behavior but also to analyze the motives and specific attributes behind different charging patterns. In our study, we consider EV drivers' socio-demographic background, such as gender, age, and settlement size (e.g., Daina et al., 2015; Pevec et al., 2020). Then, we examine how charging behavior is associated with drivers' EV routines, such as driving experience, daily mileage, and received charging guidance (e.g., Liao et al., 2023; Philipsen et al., 2018; Rauh et al., 2020). As there is a lack of insights about perceived daily charging experience as well as individual charging flexibility, we consider EV drivers' perceived ease of charging process in their routine and flexibility in terms of charging frequency and battery level at charging start.

Psychological variables have to a large extent been ignored in the context of charging behavior. Previous studies briefly noted that technology openness lowers range stress (Philipsen et al., 2019), while higher general risk propensity promotes charging with low SOC (Guo et al., 2022; Hu et al., 2019; Philipsen et al., 2018) and is related to more range stress (Philipsen et al., 2019). We include these characteristics to study them in a different context and setting, but also to test these towards a new outcome variable describing charging patterns. Thereby, general risk propensity reflects the willingness to take risks in general life, and technology openness indicates receptiveness to use new technologies. Some behavioral studies in the EV context considered ecological, economic, and social values in decision-making (e.g., Kramer et al., 2023; Schrills et al., 2020). These values can steer own behavior to be a pro-environmental, rational, and socially approved one (De Groot & Steg, 2010; Deci & Ryan, 1987). However, such values have not yet been examined in terms of revealed charging behavior. As these values could motivate reasonable charging behavior, we examined them as EV drivers' ecological awareness, economic (e.g., lower costs for charging than for fuel), and social motives (e.g., opinion of others and social norms) at EV purchase.

To fill the knowledge gap about the combined investigation of potential influencing factors on charging behavior in a nationwide setting with actual EV drivers and revealed charging behavior, we will address the following research questions:

(Q1) What are the socio-demographic characteristics of different charging behavior groups of EV drivers?

(Q2) How are EV driving- and charging-related aspects associated with different charging behavior patterns among EV drivers?

(Q3) How do psychological characteristics relate to different charging behavior patterns among EV drivers?

3. Methods

3.1. Survey and participants

This work is based on a survey of EV (exclusively BEV) drivers conducted from January to February 2024 in Norway. The EV drivers for our survey were recruited by Norstat which is a market research panel aggregator company. Being Norway's largest consumer panel, it consists of over 120,000 active participants. All respondents received 10 Norstat coins, which can be spent or donated in the Norstat store. In total 1,054 EV drivers were contacted of which 1,005 respondents completed the survey. Due to the lack of information on the true distribution of EV owners in Norway, the sample was randomly obtained based on the national distribution of gender, age, and geography, yielding a robust data set. The sample exclusively included individuals who indicated that they possess an EV. Our sample had an average age of 46.5 years (SD = 16.7, MIN = 18, MAX = 89) of which 47.76 % were female and 64.4 % had a university degree. In addition, 66.9 % were employed, and 91.34 % drove an EV that they owned by themselves or that was owned by a family member. In terms of representativity of the Norwegian population, we compared the sample characteristics to those of the population: Approximately 50 % of Norway's adult population is female (compared to 47.76 % in our study), whereas 36.9 % of all Norwegian citizens possess higher education (compared to 64.4 % in our study) which can be explained by overall higher education level among Norwegian EV driver population (Bjørge et al., 2022). The province Akershus has the highest population in Norway compared to the remaining provinces which we mirror in our sample being the highest percentage of respondents (15.42 %), whereas Finnmark is the least populous province in Norway, illustrating the smallest share in our sample (0.5 %) (Norwegian Government, 2022).

3.2. Questionnaire and measures

The questionnaire is available as a full version in the appendix. In the following, we will outline applied measures and scales of our study in more detail.

3.2.1. EV charging behavior

Charging behavior was measured by asking about five aspects of the charging routine among our respondents. In order to indicate the main charging place, participants chose between home, workplace, or public charging stations. For the usual SOC at the charging start, participants chose a range between ten different items (< 10 %, 20–10 %, 30–21 %, 40–31 %, 50–41 %, 60–51 %, 70–61 %, 80–71 %, 90–81 %, 100–91 %). Both scales, for charging location and SOC at charging start, were used by Hu et al. (2019) as two indicators of charging behavior. To specify the usual battery level at the charging end, participants chose a range between eight different items (< 30 %, 40–31 %, 50–41 %, 60–51 %, 70–61 %, 80–71 %, 90–81 %, 100–91 %). SOC at the charging end has not been studied directly, but rather through more indirect measures, such as refueling quantity preference (Philipsen et al., 2018) and charge consumption (Morrissey et al., 2016). In our study, we based the answer scale on the measurement of the SOC at the charging start. For charging frequency, the participants chose between the options "daily", "4-5 times per week", "2-3 times per week", or "rarely". This scale was adapted from previous studies by Daina et al. (2015) and Philipsen et al. (2018). Considering the preferred charging strategy, participants could choose either "I charge only when the battery level is low (less than 30 %)", "I plan for the next trip and decide if charging is necessary", "I charge whenever possible to always have a high battery level", or "I charge according to my habits/routine regardless of the current battery level". We adapted this scale from the categorization of charging strategy by Liao et al. (2023).

3.2.2. Socio-demographics

EV drivers' socio-demographics were included in the analysis for control purposesor. The participants were asked to indicate their age (in years), gender (male = 1, female = 2), and settlement size (village with <1,000 people, town with up to 100,000 people, city with up to 300,000 people, large city with > 300,000 people). In the variable measuring settlement size, every category is coded as a binary variable (0 = no, 1 = yes), while the category of a large city is the reference base. These items and scales for socio-demographics have been previously used in other related studies (e.g., Daina et al., 2015; Pevec et al., 2020).

3.2.3. EV driving- and charging-related aspects

To measure EV driving-related aspects, we asked our participants to state their EV driving experience (in years), which we used as an indicator for their practical EV-related knowledge. Previously, the EV experience has been measured based on the existence of any previous experience with EV (e.g., Pevec et al., 2020) or in the scope of a field trial (e.g., Franke et al., 2017). As previous research shows, annual mileage relates to charging frequency and SOC at charging start (e.g., Philipsen et al., 2018), we included in our study also EV drivers' daily mileage for a more granular evaluation. The EV drivers had to choose out of five different items (<5 km, 5–19 km, 20–59 km, 60–100 km, >100 km).

Items considering the participants' EV charging experience were collected using a seven-point Likert scale, ranging from 1 (not at all) to 7 (to a great extent). Thereby, we asked the participants to indicate how helpful they perceive the guidance (e.g., by their EV or charging app) in performing charging successfully. With this variable, we aimed to measure if the support and information for charging the EV drivers usually receive is sufficient and satisfying. In the relevant research, providing range- or charging-related information to drivers has been found to have a positive impact on reducing range stress and charging behavior (e.g., Rauh et al., 2015; Rauh et al., 2020). To identify EV drivers' range tolerance to low battery levels, we asked participants to evaluate, how easy it is for them to start charging at a low SOC (below 30 %). The item was adapted from the measurement of low-range aversion by Franke et al. (2017). To measure perceived charging flexibility in EV drivers' daily routine, we asked them to indicate, how easy it is for them to charge their EV less frequently if they would like to do that. With this variable, we aimed to evaluate if the EV drivers have enough charging opportunities in their daily routine (Franke & Krems, 2013) and how much flexibility to change their charging routine they potentially have.

3.2.4. Psychological characteristics

Measures considering the participants' psychological background were collected using a seven-point Likert scale, ranging from 1 (not at all) to 7 (to a great extent). For measuring the general risk propensity of EV drivers, we included the 1-item scale of the willingness to take risks by Harrison and Rutström (2008). This scale has been used in several fields to measure risk-taking behavior (e.g., Dohmen et al., 2011; Jaeger et al., 2010; Lönnqvist et al., 2015). To evaluate the technology openness of EV drivers, our questionnaire contains a 4-item scale of technology perception. This scale was derived from the measures of innovativeness by Parasuraman and Colby (2015) indicating the readiness to adopt new technologies, and of technophilia (Weyer, 1997) evaluating technology enthusiasm, skepticism, and self-assessment of competencies regarding technology use. Previously, technology perception and commitment have been studied in the context of range stress by Philipsen et al. (2019), which, thus, could be relevant to charging behavior. By combining these measures, Cronbach's alpha was 0.70 with an inter-item correlation of 0.36, which shows satisfying consistency of our scale (Tavakol and Dennick, 2011). Finally, the study included the 2-item scale of perceived ease of charging which is based on the scale for perceived ease of use by Davis (1989). Our scale included items related to whether an EV driver believes that the charging process in their routine and main charging location is usually free from effort. It yielded a Cronbach's alpha of 0.64 and a Pearson's r of 0.48, which can be considered satisfactory given the brief nature of the scale (Tavakol and Dennick, 2011).

We used the 3-item ecological awareness scale of Diekmann and Preisendörfer (1998) to evaluate the individual values and attitudes toward factors such as environmental protection, climate change, and eco-mindedness. This scale and items were used in the study by Kramer et al. (2023) to evaluate participants' environmental awareness. We found that the scale has satisfactory reliability in our sample reflected by a Cronbach's alpha of 0.92 and an inter-item correlation of 0.79 (Tavakol and Dennick, 2011). We asked the participants how important social (e.g., opinion of friends and family, status symbol) and economic factors (e.g., lower operation costs in comparison to ICE vehicles) were for them in purchasing their EVs. However, general EV purchase intention has been considered in the previous research before (e.g., Franke et al., 2017), in this study, we also aimed to evaluate purchase motives. These motives could reflect the psychological characteristics of an EV driver and hence, also their behavior regarding individual interests and social norms (e.g., De Groot & Steg, 2010; Deci & Ryan, 1987).

3.3. Latent class analysis

After analyzing descriptives about the main characteristics of the sample and controlling for the reliability of used measurement scales, we applied latent class analysis (LCA) to identify the charging behavior latent classes of the EV drivers. LCA is a powerful statistical technique that can identify distinct subgroups within a population based on observed variables (Vermunt & Magidson, 2013). As a probabilistic method, LCA can uncover (in)consistencies among variables related to charging behavior patterns (Kroesen, 2019). The measurement model within the LCA determines the optimal number of latent classes based on the shared heterogeneity among these indicators (Vermunt & Magidson, 2013).

In the LCA model, we used the five indicators of charging preferences described earlier: (1) charging place, (2) charging frequency, (3) charging strategy, (4) SOC at charging start, and (5) SOC at charging end. These variables were also used to describe the likelihood of having a specific charging behavior type, i.e., belonging to a specific latent class. The clustering is entirely determined by the shared variance among these indicators. Subsequently, the identified classes are profiled based on different covariates, such as socio-demographics, EV driving- and charging-related aspects, and psychological characteristics. This profiling allows for a deeper understanding of the identified charging patterns (Vermunt, 2010; Kroesen, 2019). To assess the associations of these covariates, we employed the 3-step procedure outlined by Vermunt (2010). This approach ensures that the covariates do not influence the measurement aspect of the model, and the classification relies solely on the indicators rather than the covariates. The 3-step procedure involves: 1) estimating the model using only the indicators (measurement model part), 2) probabilistically assigning subjects to latent classes, and 3) exploring the relationship between the identified latent class membership and covariates by using multinomial logit (MNL) model (Vermunt, 2010; Kroesen, 2019).

The primary objective of the LCA is to identify the model that captures the relationships among the indicators most effectively, with the fewest latent classes (Kroesen, 2019). To define the appropriate number of latent classes within the sample, we estimated models from one to five classes. For comparison of these models, we used goodness-of-fit measures including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Nylund et al., 2007; Vermunt, 2010), where the lowest value of AIC and BIC suggests the best model fit. Table 1 presents the goodness-of-fit measures of the five models. The three-class model had both the lowest BIC and AIC values as well as presented an even distribution ($N_{Class1} = 251$, $N_{Class2} = 368$, $N_{Class3} = 386$) into distinct and interpretable types of charging behavior. The LCA was tested using Jamovi 2.5 (Jamovi, 2024) and Stata 18 (Stata, 2023).

For the MNL model, the third class was used as the reference category, as this class contained the most observations and represented the middle of two more extreme charging behavior types. The independent variables are factors related to socio-demographic background, EV driving- and charging-related aspects, and psychological characteristics. These factors do not directly form the charging behavior but potentially differ among individuals with different charging patterns.

To address research question Q1, we included socio-demographic variables, such as age, gender, and settlement size. For research question Q2 we examined the following variables: the experience of driving an EV, daily mileage, perceived helpfulness of guidance for charging, perceived ease of charging, ease of charging at low SOC (less than 30 %), and ease of charging less frequently. Finally, to answer research question Q3, we integrated psychological variables indicating EV drivers' technology openness, general risk-propensity, ecological awareness as well as their social and economic motives in EV purchases.

4. Results

4.1. Charging behavior patterns of electric vehicle drivers

The LCA results suggest that three charging behavior classes fit the data best. Each class is described based on the summary statistics of the five indicators presented in Table 2. Here, we examine the profiles of EV drivers based on their charging behavior.

Class 1 "Daily convenient chargers": This class comprises 24.98 % (n = 251) of the sample. Individuals in this category typically charge their EVs daily. Their charging approach primarily involves charging whenever possible to always have a high battery level or whenever the opportunity arises given their routines. Charging usually commences when SOC is between 41 % and 50 % or higher and they mostly charge their EV battery full (SOC = 91 % – 100 %). Although, they are mainly home-based chargers, around 12 % of this group charge their car at the workplace, which is the highest share of workplace chargers among all classes.

Class 2 "Battery-exploiting seldom chargers": This class represents 36.62 % (n = 368) of the sample. Individuals tend to charge their EVs 2–3 times per week or less frequently, charging usually according to their driving plan and necessity, but also a notable part of 24.73 % tends to wait until the battery level is low (SOC <30 %). Charging occurs with a lower SOC (battery level of 21 %–30 %) and usually lasts until the car is fully charged (SOC = 91 %–100 %). Even though, they are mainly home-based chargers, about 12 % of this group charge their EV mainly at the public charging station, which is the highest share of public

Table 2
Summary statistics for the indicators by class (measurement model part).

Indicators	Class Class size (%)	1 24.98 %	2 36.62 %	3 38.41 %
Charging place	At home	88.05 %	86.41 %	**89.12 %**
	At workplace	**11.95 %**	1.63 %	8.03 %
	At public charging station	0.00 %	**11.96 %**	2.85 %
Charging frequency	Daily	**55.78 %**	6.79 %	3.11 %
	4–5 times per week	27.09 %	6.79 %	**29.02 %**
	2–3 times per week	10.36 %	**47.01 %**	44.56 %
	Rarely	6.77 %	**39.40 %**	23.32 %
Charging strategy	I charge only when the battery level is low (less than 30 %).	0.40 %	**41.03 %**	0.00 %
	I plan for the next trip and decide if charging is necessary.	3.59 %	50.00 %	**82.64 %**
	I charge whenever possible to always have a high battery level.	**70.12 %**	3.53 %	1.30 %
	I charge according to my habits/routine regardless of the current battery level.	**25.90 %**	5.43 %	16.06 %
SOC at the charging start	> 70 %	**13.15 %**	4.62 %	5.70 %
	70–61 %	**17.93 %**	0.27 %	4.66 %
	60–51 %	**22.31 %**	0.27 %	10.36 %
	50–41 %	23.11 %	0.54 %	**24.61 %**
	40–31 %	11.55 %	5.16 %	**44.04 %**
	30–21 %	10.76 %	**63.59 %**	10.62 %
	20 %-10 %	0.80 %	**24.73 %**	0.00 %
	< 10 %	0.40 %	**0.82 %**	0.00 %
SOC at the charging end	100–91 %	**51.39 %**	38.04 %	29.02 %
	90–81 %	15.54 %	23.91 %	**28.76 %**
	80–71 %	21.51 %	31.79 %	**35.75 %**
	70–61 %	**5.58 %**	0.54 %	1.30 %
	60–51 %	**1.99 %**	0.00 %	0.52 %
	< 50 %	3.98 %	**5.70 %**	4.66 %

Note: N = 1,005. SOC = State of Charge. Bold values indicate the highest value for each row.

Table 1
Goodness-of-fit measures of the latent class analysis model.

Number of classes	AIC	BIC	Log-Likelihood	Share of each class (and smallest class)				
				1	2	3	4	5
1	12,854	12,972	−6403	100 %				
2	12,426	12,690	−6164	62.77 %	37.23 %			
3	**12,311**	**12,667**	−6089	24.98 %	36.62 %	38.41 %		
4	12,338	12,825	−6070	38.20 %	14.10 %	24.60 %	23.10 %	
5	12,314	12,925	−6033	11.41 %	4.08 %	38.55 %	23.39 %	21.85 %

chargers among all classes.

Class 3 "Occasional battery-friendly planners": This class accounts for 38.41 % (n = 386) of the sample. Members of this class charge their EV 4–5 times per week. Many individuals in this category also plan for trips and assess the need for charging, but some charge according to their habits. Charging typically begins at a moderate SOC level of 30 % – 40 % and is interrupted at the level of 80 %, which follows a rule of thumb for battery-friendly charging (e.g., Semanjski & Gautama, 2016; Werner et al., 2021). In this class, we find the most home-based EV chargers compared to the other classes.

4.2. Descriptive statistics among charging behavior patterns

Table 3 shows descriptive statistics for the explanatory variables and the significance of their independence among the three classes based on ANOVA or Chi-Square test, for continuous and categorical variables respectively.

According to Table 3, there are on average no significant difference between classes regarding age and gender of respondents. Individuals in class 1 live mostly in settlements with 1,000–20,000 inhabitants, whereas those in classes 2 and 3 live mostly in a city with a population between 20,000 and 100,000 people. The average EV driving experience does not differ significantly across classes. The daily mileage is slightly lower for classes 1 and 3 than for class 2. Participants in class 3 perceive on average slightly more helpfulness of charging guidance (e.g., via car or mobile app) than the other two groups. The means for perceived ease of charging process at the EV drivers' main charging location are not significantly different across classes. Generally, drivers in class 2 report higher flexibility to postpone charging until SOC is below 30 % than those in classes 1 and 3. However, individuals in class 2 are less keen on charging even less frequently than they already do compared to their peers in the other two classes. Technology openness is on average the lowest for class 1, moderately higher for class 2, and the highest for class 3. Considering average values for general risk propensity, the three classes do not have significant differences. The social motive for EV purchase is on average the lowest in class 1, followed by class 2 and class 3. For the average values in the economic motive of EV purchase, there are no significant differences between classes. We successfully tested all our explanatory variables against violations of multicollinearity (average VIF = 1.14) (Daoud, 2017).

4.3. Analysis of the MNL model

Table 4 shows the estimated parameters of the MNL model. We used these findings to address the research questions regarding the socio-demographics (Q1), EV driving- and charging-related aspects (Q2), and psychological characteristics (Q3). Furthermore, we explore their importance in forming the charging patterns in combination with other variables in the model.

The EV drivers who are male are significantly more likely to be in class 1 compared to class 3. However, we can not find any significant differences between these classes in terms of age and settlement size, nor any significant evidence for a difference between classes 2 and 3 regarding all three socio-demographic values. Furthermore, individuals who have more experience driving an EV and have higher daily mileage are significantly more likely to be in class 1 compared to class 3. EV drivers who have lower daily mileage are significantly more likely to be in class 2 than in class 3. However, we do not find any significant evidence for a difference between classes 2 and 3 regarding the length of EV experience. The results indicate that EV drivers who receive helpful guidance for charging are more likely to belong to class 3 than to the other two classes. Yet, we do not find any statistical evidence that EV drivers who perceive higher ease of charging are less or more likely to belong to class 3 than to class 1 and class 2, respectively. We find that EV drivers who feel comfortable about charging their car less frequently than they currently do are less likely to belong to class 3 than to class 1, although more likely to class 3 than to class 2. Our results indicate that EV drivers who feel comfortable about starting to charge at low SOC are more likely to be in class 3 than in class 1, but less likely in class 3 than in class 2.

Our findings on psychological variables indicate that EV drivers who are more open to new technology are more likely to belong to class 3 than to class 1. However, we can not find any evidence that technology openness differs between drivers in class 3 and class 2. We find that EV drivers with lower general risk propensity are more likely to be in class 3

Table 3
Descriptive statistics of explanatory variables by charging class.

Variable	Min	Max	Class 1 (n = 251)	Class 2 (n = 368)	Class 3 (n = 386)	ANOVA/ Chi^2
Age (in years), M (SD)	18	89	45.56 (15.58)	46.91 (17.13)	46.83 (17.00)	–
Gender, % (n)	1	2				–
Male (1)			57.37 % (155)	50.82 % (187)	50.26 % (194)	
Settlement size, % (n)	1	4				**
< 1,000 people			11.16 % (28)	5.98 % (22)	10.10 % (39)	
1,000 – 20,000 people			34.26 % (86)	24.18 % (89)	25.65 % (99)	
20,000 – 100,000 people			31.08 % (78)	36.68 % (135)	37.82 % (146)	
> 100,000 people			23.51 % (59)	33.15 % (122)	26.42 % (102)	
EV experience (years), M (SD)	0^{α}	15	4.13 (2.78)	3.73 (2.75)	3.80 (2.77)	–
Daily mileage, % (n)	1	5				***
< 5 km (< 3 miles)			10.36 % (26)	16.58 % (61)	13.47 % (52)	
5 – 19 km (3 – 12 miles)			27.89 % (70)	45.11 % (166)	41.45 % (160)	
20 – 59 km (12 – 37 miles)			41.43 % (104)	31.79 % 117	32.90 % (127)	
60 – 99 km (37 – 62 miles)			13.55 % (34)	5.16 % (19)	7.77 % (30)	
> 100 km (> 62 miles)			6.77 % (17)	1.36 % (5)	4.40 % (17)	
Perceived helpful charging guidance, M (SD)	1	7	5.21 (1.79)	5.14 (1.57)	5.52 (1.42)	*
Perceived ease of charging, M (SD)	1	7	5.80 (1.28)	5.77 (1.36)	5.85 (1.16)	–
Ease of charging at low SOC, M (SD)	1	7	3.76 (2.08)	5.47 (1.61)	4.40 (1.83)	***
Ease of charging less frequently, M (SD)	1	7	4.64 (1.78)	4.08 (1.69)	4.52 (1.54)	***
Technology openness, M (SD)	1	7	3.86 (1.18)	3.99 (1.14)	4.11 (1.16)	*
General risk propensity, M (SD)	1	7	3.71 (1.41)	3.73 (1.33)	3.53 (1.26)	–
Ecological awareness, M (SD)	1	7	4.62 (1.67)	4.90 (1.52)	5.00 (1.58)	*
Social EV purchase, M (SD)	1	7	2.13 (1.29)	2.52 (1.46)	2.58 (1.46)	**
Economic EV purchase, M (SD)	1	7	4.80 (0.68)	4.77 (0.73)	4.85 (0.49)	–

Note: EV = Electric Vehicle, SOC = State of Charge,
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, – not significant, α less than a year.

Table 4
Results of multinomial logit model.

Variable	Class	Coefficient	Standard Error	z-score	95 % Confidence Interval
Age	1	−0.01	0.01	−1.88	[−0.02; 0.00]
	2	0.01	0.01	1.67	[−0.00; 0.02]
Gender (2 = Female)	1	−0.43*	0.19	−2.29	[−0.81; −0.06]
	2	−0.02	0.17	−0.14	[−0.36; 0.31]
Settlement size	1	−0.08	0.09	−0.85	[−0.26; 0.10]
	2	0.15	0.09	1.74	[−0.02; 0.32]
EV experience	1	0.06*	0.03	2.06	[0.00; 0.12]
	2	−0.02	0.03	−0.73	[−0.08; 0.04]
Daily mileage	1	0.29**	0.09	3.18	[0.11; 0.47]
	2	−0.22*	0.09	−2.44	[−0.39; −0.04]
Perceived helpful charging guidance	1	−0.13*	0.06	−2.05	[−0.25; −0.01]
	2	−0.11*	0.06	−2.00	[−0.22; −0.00]
Perceived ease of charging	1	0.06	0.06	0.80	[−0.09; 0.21]
	2	−0.13	0.07	−1.79	[−0.27; 0.01]
Ease of charging less frequently	1	0.17**	0.05	3.08	[0.06; 0.28]
	2	−0.22***	0.05	−4.33	[−0.32; −0.12]
Ease of charging at low SOC	1	−0.21***	0.05	−4.43	[−0.30; −0.11]
	2	0.40***	0.05	8.33	[0.30; 0.49]
Technology openness	1	−0.28**	0.08	−3.29	[−0.44; −0.11]
	2	−0.08	0.08	−1.00	[−0.23; 0.07]
General risk propensity	1	0.14*	0.07	1.98	[0.00; 0.27]
	2	0.14*	0.06	2.20	[0.02; 0.27]
Ecological awareness	1	−0.09	0.06	−1.59	[−0.20; 0.02]
	2	−0.02	0.05	−0.29	[−0.12; 0.09]
Social EV purchase	1	−0.22***	0.06	−3.49	[−0.35; −0.10]
	2	−0.02	0.06	−0.31	[−0.13; 0.09]
Economic EV purchase	1	−0.07	0.14	−0.48	[−0.35; 0.21]
	2	−0.13	0.13	−0.96	[−0.39; 0.13]

Note: N = 1,005. EV = Electric Vehicle, SOC = State of Charge.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
Class 1 = Daily convenient charger, Class 2 = Battery-exploiting seldom charger, Class 3 = Occasional battery-friendly planner (reference base).

than in class 1 and class 2, respectively. Those who have been more socially driven at the EV purchase are significantly more likely to be in class 3 compared to class 1. We can not find any significant differences between the first and third classes in terms of the level of ecological awareness as well as the economic motive of EV purchase. Also, we do not find any significant evidence for a difference between classes 2 and 3 regarding ecological awareness and both EV purchase motives.

5. Discussion

5.1. Research implications

One of the important insights of our study is the three identified EV charging patterns. There are daily convenient chargers who prefer keeping the battery full at every opportunity and charging mainly at home or work. This group of EV drivers likely values the convenience of always having a full battery and the ability to charge whenever it is most accessible to them. EV drivers in this group probably plug in their EVs every time they reach home or arrive at work to use each charging opportunity and avoid making further thoughts about charging in advance. Then, there are battery-exploiting seldom chargers who procrastinate until SOC is very low but then charge full, usually at home or in a public space. This group of EV drivers may be more focused on maximizing the usage of their battery before recharging, even if it means letting the battery reach a very low SOC. Particularly, due to some share of EV drivers who charge mainly in public spaces, they seem to accept low SOC in exchange for less overhead to plan and carry out charging more than needed. However, most EV drivers are occasional battery-friendly planners who plan their charging needs, charge mainly at home, and keep their battery level between 40 % and 80 %. This pattern contributes not only to a more balanced use of the electricity grid (e.g., Mathur and Yemula, 2018), but also to battery longevity (e.g., Werner et al., 2021), and thus follows the most optimal charging pattern. The dominance of this group could be explained by a particularly high share of home-based charging in Norway, wide use of cost- and consumption-optimized smart charging in Norwegian households, but also by their well-established electric mobility (Bjørndal et al., 2023). Due to a mixture of employed charging strategies and measured behavior within the classes, the charging style is driven by individual circumstances and further characteristics of EV drivers. These aspects could be explained by the variables we included and tested as covariates in our analysis.

Contrary to previous studies (e.g., Daina et al., 2015; Pevec et al., 2020), we could not find that age and settlement have a significant effect on charging patterns. Probably, as compared to other studies, we investigated a revealed charging behavior with a diverse population-based sample rather than the stated preferences of a few EV drivers in a developing EV context. Furthermore, our study showed that instead of age, rather the EV driving experience plays a significant role in forming charging behavior. Precisely, drivers with longer EV experience are more likely to be convenient daily chargers than battery-friendly planners. According to Liao et al. (2023), inexperienced EV drivers follow a more need-based than habit- or opportunity-based charging pattern. This could imply that those who started driving EVs later, have higher availability to the latest features for optimal charging, require more effort to carry out charging, or do not have a predefined routine yet. The insignificance of settlement size on charging behavior could be explained by a high share of residential charging in Norway (Schulz & Rode, 2022). The availability of the secure option of home charging makes EV drivers less influenced by their settlement and the local charging infrastructure. Thereby, the overall EV-friendly environment in Norway could be a driver for above-average perceived ease of charging process among all three classes regardless of their main charging location.

We found that the male gender and frequent commute increase the likelihood of being a daily convenient charger rather than an occasional battery-friendly planner. Possibly, since female drivers often have more commitments related to family (Sovacool et al., 2019), they prefer plan-based and safe home charging. Meanwhile, male drivers seem to travel longer distances and have to count on intermediate charging at work. This argumentation is supported by a higher general risk propensity among daily convenient chargers compared to battery-friendly planners. Interestingly, drivers who are open to charging less frequently than they currently do, are more likely to belong to daily convenient chargers despite their opportunity-chasing charging strategy. It seems that they do not charge frequently because of a higher risk aversion (e.g., Philipsen et al., 2019) or less EV experience (e.g., Rauh et al., 2015). Instead, their charging frequency is due to their commuting EV routine and need for convenience, which is also reflected by their avoidance of low SOC and lower openness to deal with new technology. Seldom chargers were willing to take more risks as well and were as technology open as battery-friendly planners. Aligned with their lower daily mileage, they are comfortable with seldom charging despite more reliance on public charging and dealing with external charging technology. EV drivers in the seldom battery-exploiting class are less flexible to charge even less frequently than they currently do, which can be explained by their overall low SOC at the charging start and low charging frequency.

Moreover, our findings show that there is a positive relationship between provided charging information (e.g., in an app or the vehicle) with more sustainable and rational charging behavior, in addition to previously found lowering effect on range anxiety (e.g., Franke et al., 2017; Rauh et al., 2020). We could not find any support that ecological awareness or having been economically motivated in EV purchase would indicate more optimal charging behavior. This does not imply that these individual values are overall unimportant, but rather that these are less substantial than other factors in explaining charging patterns. However, those who were more socially driven when buying their EV belonged more likely to occasional battery-friendly chargers than to daily convenient chargers. Perhaps, their optimal charging behavior is driven by their stronger responsiveness towards societal norms and expectations.

5.2. Practical implications

Firstly, it is important to differentiate between flexible, convenient, and rational EV drivers to consider their specific needs and impact on the charging infrastructure. As in our findings access to home/workplace charging is associated with more convenient and habit-based charging behavior, the availability of Level 2 chargers (up to 22 kW) in residential and commercial settings could protect the battery despite its frequent re-charging. As those using more public charging revealed a low-range-driven behavior, the industry could prioritize the deployment of public charging stations in strategic locations (e.g., shopping malls, office areas, and sports centers). This could help to ensure easy access to charging and combine it with daily time-requiring activities. Due to the high perceived ease of charging among all charging patterns, it seems that Norwegian policies for the expansion of charging points and clear standards for their interoperability (Figenbaum, 2017) have been very successful. This could serve as a baseline for other countries that are in the development of their charging infrastructure and electric mobility environment.

Our most rational charger type keeps the SOC on an optimal level of 40–80 %, plans to charge in advance, and charges mainly at home. This kind of behavior is typical for smart charging use. A smart charging system optimizes EV charging based on electricity price and consumption and is increasingly popular in Norwegian households (Bjørndal et al., 2023). Piloting and scaling of this and other charging technologies, such as vehicle-to-grid (V2G) which enables EVs to transfer electricity back to the power network (Mehdizadeh et al., 2024), could further contribute to grid balance and the use of renewable energies. Especially in Norway, where the EV market has been rapidly growing, policies for ensuring reliable charging infrastructure and efficient energy management have become crucial. Thereby, uncoordinated charging of daily convenient chargers increases electricity consumption during the morning and evening peaks and has impacts on the distribution network (e.g., Wangsness & Halse, 2021). Norwegian policymakers sought to counteract this behavior by introducing dynamic grid tariffs which encourage consumers to adjust their electricity consumption in response to fluctuating prices and thus, reduce peaks loads (Winther & Sundet, 2023).

Through combination of intelligent charging functions with helpful charging guidance, automakers could further steer optimal charging behavior by making it more feasible, comprehensible, and integrable regardless of their routine, technology interest, and EV experience. Charging-related information and support could be particularly enhanced for EV drivers relying on workplace or public charging infrastructure, as in the classes of daily convenient chargers and battery-exploiting occasional chargers. Providing EV drivers with real-time information on the availability and estimated charging times of workplace or public charging stations could help them better plan their charging needs. Developing intuitive and user-friendly charging apps and in-vehicle information could provide real-time suggestions based on individual driving needs and charging flexibility. Further, by using nudging techniques in charging and in-car applications network providers and automakers could motivate sustainable charging behavior, as in the class of occasional battery planners, more effectively. For example, they could suggest default charging settings, provide contingency rewards for optimal charging behavior and peer-based local community comparisons.

5.3. Limitations and future work

Even though we attempted to conduct our study as accurately as possible, it bears some limitations. Unlike an experimental design with randomization to an intervention and control group, or a panel with longitudinal data collected in a series of repeated observations, our study relies on cross-sectional survey data. This approach only yields correlational results, rather than establishing causal relationships. Our non-experimental design may have introduced omitted variable bias, which could lead to endogeneity issues (e.g., Wilms et al., 2021). As a result, we are unable to draw causal inferences from the findings of our study. However, questionnaire study is an acknowledged method to gather information to explore aspects of a novel topic (Kelley et al., 2003), which has been used in related to charging behavior as well (e.g., Daina et al., 2015; Philipsen et al., 2018). Further, our study was conducted in Norway, where EV adoption and the usage of price-based smart charging systems are among the highest (Bjørndal et al., 2023; Statista, 2023). The use of smart charging technologies was the reason, why we did not ask participants about the timing of their charging sessions, as their plug-in time could substantially differ from the actual charging time. Due to dynamic electricity tariffs in Norway (Winther & Sundet, 2023), it was difficult to capture charging prices by a questionnaire study, because electricity prices fluctuate from hour to hour depending on the current grid power capacity and the electricity demand. Hence, the results can be generalized only to regions with similar contexts, such as Scandinavian countries and the Netherlands. However, the findings from Norway serve as indicators for the future development of the overall EV market. Some variables which we did not consider in the present study, such as vehicle use and size may have influenced the charging patterns in ways not fully captured by the study and could have introduced heterogeneity in the results.

Future research in the field of EV charging holds several opportunities for enhancing the individual charging experience as well as the academic landscape in this field. One example is to study user design for mobility products which are specifically tailored to meet the diverse needs of EV drivers. Understanding the motives behind convenient and flexible charging behavior among EV drivers is key to helping develop targeted interventions and incentives to encourage more sustainable charging practices. Particularly, investigating the psychology behind range anxiety can provide valuable insights to address concerns impeding optimal charging behavior. In addition, future research could focus on identifying strategies to educate and empower EV drivers, enabling them to make informed decisions that balance their charging needs with energy sustainability. Gamification approaches rewarding sustainable charging habits could further motivate EV drivers to optimize their charging routine.

6. Conclusion

The objective of our study was to identify patterns in revealed charging behavior as well as to examine the influence of socio-demographics, EV driving- and charging-related aspects, and psychological background on these patterns. Based on the survey with 1,005 Norwegian EV drivers, we provide valuable insights from a country with well-developed electric mobility.

Based on charging frequency, location, strategy, and SOC at charging, we identified three distinct charging classes – daily convenient chargers, battery-exploiting seldom chargers, and occasional battery-friendly planners. Considering the effect on charging infrastructure and battery health, the third group implies the optimal charging pattern. EV drivers who are male, more experienced, have a higher daily mileage, and perceive guidance for charging as less helpful, are more likely to make daily convenient charges compared to the reference group of occasional battery-friendly planners. In addition, individuals being potentially comfortable charging less frequently as they currently do, but are less prone to start charging at a low SOC, illustrate lower technology openness, higher general risk propensity, and were less socially influenced at the EV purchase, belong more likely to daily convenient chargers than to the reference group. Further, those who have lower daily mileage and perceive charging guidance as less helpful, are more likely to be battery-exploiting seldom chargers than occasional battery-friendly planners. Individuals who find it easy to charge at a low SOC but difficult to charge even less frequently than they currently do, and illustrate a higher general risk propensity, are more likely to belong to the group of battery-exploiting seldom chargers than to the reference group.

Overall, our findings suggest that a combination of individual, technological, and contextual factors play a significant role in shaping EV charging patterns. To handle the diverse needs of convenient, flexible, and rational chargers while enabling seamless sustainable charging, it is crucial to expand workplace and public charging infrastructure, provide reliable and comprehensive charging information, and introduce policies encouraging integration of smart charging and V2G technologies. Particularly, experienced, male, frequently commuting, and conservative EV drivers could be convinced to enhance their charging patterns.

CRediT authorship contribution statement

Junianna Zatsarnaja: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Milad Mehdizadeh:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Katharina Reiter:** Conceptualization, Methodology, Writing – review & editing. **Alim Nayum:** Conceptualization, Methodology, Writing – review & editing. **Trond Nordfjærn:** Conceptualization, Methodology, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Questionnaire

- How many years have you been driving an EV in general (in years)? [open answer field, maximum value: 15]
- How important were the following factors for you to purchase an EV? (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and scale 7 means "to a great extent")
  a. Ecological reasons (e.g., reduced CO2 footprint)
  b. Technological reasons (e.g., interest in emerging technologies)
  c. Economic reasons (e.g., lower operation costs in comparison to combustion vehicles)
  d. Political reasons (e.g., well-established charging infrastructure)
  e. Social reasons (e.g., opinion of friends and family, status symbol)
- Approximately how many kilometers do you usually drive with your EV daily? (Please choose one option)
  a. < 5 km
  b. 5–9 km
  c. 10–19 km
  d. 20–39 km
  e. 40–59 km
  f. 60–79 km
  g. 80–100 km
  h. > 100 km
- Where do you mainly charge? (Please choose one option)
  a. At home
  b. At the workplace
  c. At a public charging station
- How often do you charge in everyday life at your main charging point? (Please choose one option)
  a. Daily
  b. 4–5 times per week
  c. 2–3 times per week
  d. Rarely
- What is your most common charging strategy? (Please choose one option)
  a. I charge only when the battery level is low (less than 30 %).
  b. I plan for the next trip and decide if charging is necessary.
  c. I charge whenever possible to always have a high battery level.
  d. I charge according to my habits/routine regardless of the current battery level.
- At what State of Charge (SOC) do you usually start to charge your EV? (Please choose one option)
  a. 100–91 %
  b. 90–81 %
  c. 80–71 %
  d. 70–61 %
  e. 60–51 %
  f. 50–41 %
  g. 40–31 %
  h. 30–21 %
  i. 20–10 %
  j. < 10 %
- Until which State of Charge (SOC) do you usually charge your EV? (Please choose one option)
  a. 100–91 %
  b. 90–81 %
  c. 80–71 %
  d. 70–61 %
  e. 60–51 %
  f. 50–41 %
  g. 40–30 %
  h. <30 %
- For me to only plug in my car at the State of Charge (SOC) lower than 30 % is very difficult (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and scale 7 means "to a great extent").
- If I wanted to, it would be easy for me to charge my car less frequently (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and scale 7 means "to a great extent").
- I Receive enough helpful guidance in performing charging successfully (e.g., by my car or charging app). (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and scale 7 means "to a great extent")
- Ecology (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and 7 means "to a great extent")
  a. I Worry about the environmental conditions we will live under in the future
  b. If we continue with business as usual, we are heading for major environmental problems.
  c. In favor of the environment, we should all be prepared to limit our living standards.
- Risk (Please rate on a scale from 1 to 7 where 1 means "not at all" and 7 means "to a great extent")
  a. How much are you willing to take risks in your everyday life?
- Technology perception (Please rate every item on a scale from 1 to 7 where 1 means "not at all" and scale 7 means "to a great extent")
  a. Other people come to me for advice on new technologies.
  b. In general, I am among the first in my circle of friends to acquire new technology when it appears.
  c. When I acquire a new technological device, I am soon familiar with its functions.
  d. I rather stick to conventional technology which already proved to be working

- Perceived ease of use (Please rate every item on a scale from 1 to 7 where 1 means “not at all” and scale 7 means “to a great extent”)
  a. Interacting with the charging system at my main charging location is often frustrating.
  b. Charging my electric car requires a lot of mental effort.
- Control beliefs (Please rate every item on a scale from 1 to 7 where 1 means “not at all” and scale 7 means “to a great extent”)
  a. Having enough remaining range in my car is entirely up to me.
  b. I feel in complete control over the State of charge (SOC) of my car
- What is your age? (Please choose one option)
  a. 18 – 24 years
  b. 25 – 34 years
  c. 35 – 44 years
  d. 45 – 54 years
  e. 55 – 64 years
  f. Above 64 years
- What is your gender? (Please choose one option)
  a. Male
  b. Female
- What is your working status? (Please choose one option)
  a. Student
  b. Employed
  c. Unemployed
  d. Retired
  e. Disabled/rehabilitation
  f. Homewife/husband
- What is your highest level of education? (Please choose one option)
  a. Primary or secondary school.
  b. High school.
  c. University/college.
  d. Other.
- How would you describe the place where you live? (Please choose one option)
  a. Village (population less than 1,000).
  b. Town (population between 1,000 and 100,000).
  c. City (population between 100,000 and 300,000).
  d. Large city (population between 300,000 and 1 million).
- Do you own or lease the EV you usually drive? (Please choose one option)
  a. I am the owner of the EV.
  b. My family member is the owner of the EV.
  c. I am the leaseholder of the EV.
  d. My family member is the leaseholder of the EV.
  e. I drive a company car.
  f. Other.

References

Alaee, P., Bems, J., Anvari-Moghaddam, A., 2023. A Review of the latest Trends in Technology and Economic Aspects of EV Charging Management. Energies 16 (9), 3669. https://doi.org/10.3390/en16093669.

Bjørge, N.M., Hjelkrem, O.A., Babri, S., 2022. Characterization of norwegian battery electric vehicle owners by level of adoption. World Electric Vehicle J. 13 (8), 150. https://doi.org/10.3390/wevj13080150.

Bjørndal, E., Bjørndal, M., Bøe, E.K., Dalton, J., Guajardo, M., 2023. Smart home charging of electric vehicles using a digital platform. Smart Energy 12, 100118. https://doi.org/10.1016/j.segy.2023.100118.

Bühler, F., Cocron, P., Neumann, I., Franke, T., Krems, J.F., 2014. Is EV experience related to EV acceptance? Results from a German field study. Transport. Res. F: Traffic Psychol. Behav. 25, 34–49. https://doi.org/10.1016/j.trf.2014.05.002.

Chakraborty, D., Bunch, D.S., Lee, J.H., Tal, G., 2019. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transp. Res. Part D: Transp. Environ. 76, 255–272. https://doi.org/10.1016/j.trd.2019.09.015.

Daina, N., Polak, J.W., Sivakumar, A., 2015. Patent and latent predictors of electric vehicle charging behavior. Transp. Res. Rec. 2502 (1), 116–123. https://doi.org/10.3141/2502-14.

Daina, N., Sivakumar, A., Polak, J.W., 2017. Modeling electric vehicles uses a survey on the methods. Renew. Sustain. Energy Rev. 68, 447–460. https://doi.org/10.1016/j.rser.2016.10.005.

Daoud, J.I., 2017. Multicollinearity and regression analysis. J. Phys. Conf. Ser. 949 (1), 012009. https://doi.org/10.1088/1742-6596/949/1/012009.

Davis, F.D., 1989. Technology acceptance model: TAM. Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption, 205(219), 5.

De Groot, J.I., Steg, L., 2010. Relationships between value orientations, self-determined motivational types, and pro-environmental behavioral intentions. J. Environ. Psychol. 30 (4), 368–378. https://doi.org/10.1016/j.jenvp.2010.04.002.

Deci, E.L., Ryan, R.M., 1987. The support of autonomy and the control of behavior. J. Pers. Soc. Psychol. 53, 1024–1037. https://doi.org/10.1037//0022-3514.53.6.1024.

Diekmann, A., Preisendörfer, P., 1998. Environmental behavior: discrepancies between aspirations and reality. Ration. Soc. 10 (1), 79–102. https://doi.org/10.1177/104346398010001004.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9 (3), 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x.

Fieltsch, P., Flämig, H., Rosenberger, K., 2020. Analysis of charging behavior when using battery electric vehicles in commercial transport. Transp. Res. Procedia 46, 181–188. https://doi.org/10.1016/j.trpro.2020.03.179.

Figenbaum, E., 2017. Perspectives on Norway’s supercharged electric vehicle policy. Environ. Innov. Soc. Trans. 25, 14–34. https://doi.org/10.1016/j.eist.2016.11.002.

Franke, T., Krems, J.F., 2013. Understanding charging behaviour of electric vehicle users. Transport. Res. F: Traffic Psychol. Behav. 21, 75–89. https://doi.org/10.1016/j.trf.2013.09.002.

Franke, T., Günther, M., Trantow, M., Krems, J.F., 2017. Does this range suit me? range satisfaction of battery electric vehicle users. Appl. Ergon. 65, 191–199. https://doi.org/10.1016/j.apergo.2017.06.013.

Guo, Y., Qian, X., Lei, T., Guo, S., Gong, L., 2022. Modeling the preference of electric shared mobility drivers in choosing charging stations. Transp. Res. Part D: Transp. Environ. 110, 103399. https://doi.org/10.1016/j.trd.2022.103399.

Hajhashemi, E., Sauri Lavieri, P., Nassir, N., 2024. Modelling interest in co-adoption of electric vehicles and solar photovoltaics in Australia to identify tailored policy needs. Sci. Rep. 14 (1), 9422. https://doi.org/10.2139/ssrn.4559022.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transp. Res. Part D: Transp. Environ. 62, 508–523. https://doi.org/10.1016/j.trd.2018.04.002.

Harrison, G.W., Elisabet Rutström, E., 2008. Risk aversion in the laboratory. Research in Experimental Economics 12, 41–196. https://doi.org/10.1016/S0193-2306(08)00003-3.

Helmus, J.R., Vogel, I.S., van den Hoed, R., 2020. Exploring social charging behavior between ev users in sharing charging points. 33rd Electric Vehicle Symposium (EVS33). Portland, Oregon, June 14 - 17, 2020, 10.1109/ITEC.2019.8790534.

Hu, L., Dong, J., Lin, Z., 2019. Modeling charging behavior of battery electric vehicle drivers: a cumulative prospect theory based. Transp. Res. Part C Emerging Technol. 102, 474–489. https://doi.org/10.1016/j.trc.2019.03.027.

Huang, Y., Jiang, R., Pei, J., Liang, S., Song, J., Ju, Y., Zhang, C., 2024. Analyzing EV charging patterns: towards efficient infrastructure deployment. Adv. Eng. Technol. Res. 11 (1), 158. https://doi.org/10.56028/aetr.11.1.158.2024.

International Energy Agency. (2024). Global EV Outlook 2024. Retrieved from . Accessed on June 29, 2024.

Jaeger, D.A., Dohmen, T., Falk, A., Huffman, D., Sunde, U., Bonin, H., 2010. Direct evidence on risk attitudes and migration. Rev. Econ. Stat. 92 (3), 684–689. https://doi.org/10.1162/REST_a_00020.

Jamovi project (2024). *jamovi* (Version 2.5) [Computer Software]. Retrieved from https://www.jamovi.org. Accessed on July 21, 2024.

Kelley, K., Clark, B., Brown, V., Sitzia, J., 2003. Good practice in the conduct and reporting of survey research. Internat. J. Quality Health Care 15 (3), 261–266. https://doi.org/10.1093/intqhc/mzg031.

Khaleghikarahrodi, M., Macht, G.A., 2023. Patterns, no patterns, that is the question: Quantifying users’ electric vehicle charging. Transport Policy 141, 291–304. https://doi.org/10.1016/j.tranpol.2023.07.020.

Khaleghikarahrodi, M., Macht, G.A., 2024. Rush to charge, dead to drive: application of deadline rush model to electric vehicle user’s charging behavior. Human Factors. https://doi.org/10.1177/0018720824123608.

Kramer, J., Riza, L., Petzoldt, T., 2023. Carbon savings, fun, and money: the effectiveness of multiple motives for eco-driving and green charging with electric vehicles in Germany. Energy Res. Soc. Sci. 99, 103054. https://doi.org/10.1016/j.erss.2023.103054.

Kroesen, M., 2019. Is active travel part of a healthy lifestyle? Results from a latent class analysis. J. Transport Health 12, 42–49. https://doi.org/10.1016/j.jth.2018.11.006.

Lee, J.H., Chakraborty, D., Hardman, S.J., Tal, G., 2020. Exploring electric vehicle charging patterns: mixed usage of charging infrastructure. Transport. Res. Part d: Transport Environ. 79, 102249. https://doi.org/10.1016/j.trd.2020.102249.

Liao, Y., Tozluoğlu, Ç., Sprei, F., Yeh, S., Dhamal, S., 2023. Impacts of charging behavior on BEV charging infrastructure needs and energy use. Transport. Res. Part d: Transport Environ. 116, 103645. https://doi.org/10.1016/j.trd.2023.103645.

Lönnqvist, J.E., Verkasalo, M., Walkowitz, G., Wichardt, P.C., 2015. Measuring individual risk attitudes in the lab: Task or ask? An empirical comparison. J. Econ. Behav. Org. 119, 254–266. https://doi.org/10.1016/j.jebo.2015.08.003.

Mathur, A.K., Yemula, P.K., 2018. Optimal charging schedule for electric vehicles in parking lot with solar power generation. In: 2018 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia). IEEE, pp. 611–615, 10.1109/ISGT-Asia.2018.8467916.

Mehdizadeh, M., Nayum, A.N., Klöckner, C.A., 2024. Are Norwegian car users ready for a transition to vehicle-to-grid technology? Transport Policy 146, 126–136. https://doi.org/10.1016/j.tranpol.2023.11.014.

Morrissey, P., Weldon, P., O'Mahony, M., 2016. Future standard and fast charging infrastructure planning: an analysis of electric vehicle charging behaviour. Energy Policy 89, 257–270. https://doi.org/10.1016/j.enpol.2015.12.001.

Nazari, Z., Musilek, P., 2024. Uncovering patterns in electric vehicle charging: a data-driven approach. In: 2024 IEEE Power & Energy Society General Meeting (PESGM). IEEE, pp. 1–5.

Neubauer, J., Wood, E., 2014. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility. J. Power Sour. 257, 12–20. https://doi.org/10.1016/j.jpowsour.2014.01.075.

Norwegian Government. (2022). Fylkesinndelingen fra 2024. Retrieved from . Accessed on June 29, 2024.

Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct. Equation Model. Multidiscip. J. 14 (4), 535–569. https://doi.org/10.1080/10705510701575396.

Parasuraman, A., Colby, C.L., 2015. An updated and streamlined technology readiness index: TRI 2.0. J. Service Res. 18 (1), 59–74. https://doi.org/10.1177/1094670514539730.

Pevec, D., Babic, J., Carvalho, A., Ghiassi-Farrokhfal, Y., Ketter, W., Podobnik, V., 2020. A survey-based assessment of how existing and potential electric vehicle owners perceive range anxiety. J. Cleaner Product. 276, 122779. https://doi.org/10.1016/j.jclepro.2020.122779.

Philipsen, R., Brell, T., Brost, W., Eickels, T., Ziefle, M., 2018. Running on empty–users' charging behavior of electric vehicles versus traditional refueling. Transport. Res. Part F: Traffic Psychol. Behav. 59, 475–492. https://doi.org/10.1016/j.trf.2018.09.024.

Philipsen, R., Brell, T., Biermann, H., Ziefle, M., 2019. Under pressure – users' perception of range stress in the context of charging and traditional refueling. World Electric Vehicle J. 10 (3), 50. https://doi.org/10.3390/wevj10030050.

Rauh, N., Franke, T., Krems, J.F., 2015. Understanding the impact of electric vehicle driving experience on range anxiety. Hum. Factors 57 (1), 177–187.

Rauh, N., Günther, M., Krems, J.F., 2020. Positive influence of practical electric vehicle driving experience and range related knowledge on drivers' experienced range stress. Research Part F: Traffic Psychol. Behav. 71, 182–197. https://doi.org/10.1016/j.trf.2020.03.013.

Schulz, F., Rode, J., 2022. Public charging infrastructure and electric vehicles in Norway. Energy Policy 160, 112660. https://doi.org/10.1016/j.enpol.2021.112660.

Schrills, T., Zoubir, M., Stahl, J., Drozniak, K., Franke, T., 2020. Good boy here or bad boy far away? In: Harris, D., Li, W.C. (Eds.), Engineering Psychology and Cognitive Ergonomics. Cognition and Design. HCII 2020. Springer, Cham, pp. 398–411, 10.1007/978-3-030-49183-3_31.

Semanjski, I., Gautama, S., 2016. Forecasting the state of health of electric vehicle batteries to evaluate the viability of car sharing practices. Energies 9 (12), 1025. https://doi.org/10.3390/en9121025.

Sovacool, B.K., Kester, J., Noel, L., de Rubens, G.Z., 2019. Income, political affiliation, urbanism and geography in stated preferences for electric vehicles (EVs) and vehicle-to-grid (V2G) technologies in Northern Europe. J. Transport Geogr. 78, 214–229. https://doi.org/10.1016/j.jtrangeo.2019.06.006.

Sprei, F., Kempton, W., 2024. Mental models guide electric vehicle charging. Energy 292, 130430. https://doi.org/10.1016/j.energy.2024.130430.

StataCorp, 2023. Stata Statistical Software: Release 18 [Computer software]. StataCorp LLC, College Station, TX.

Statista. (2023). Electric Mobility: Norway Leads the Charge. Retrieved from https://www.statista.com/chart/17344/electric-vehicle-share/. Accessed on June 28, 2024.

Statista. (2024a). Estimated plug-in electric light vehicle sales worldwide from 2015 to 2023. Retrieved from https://www.statista.com/statistics/665774/global-sales-of-plug-in-light-vehicles/. Accessed on June 29, 2024.

Statista. (2024b). Share of electric cars among passenger cars in Germany from 2014 to 2024. Retrieved from https://www.statista.com/statistics/1300500/electric-cars-share-in-germany/. Accessed on June 29, 2024.

Statistics Norway. (2024). Registered Vehicles. Retrieved from . Accessed on June 29, 2024.

Tavakol, M., Dennick, R., 2011. Making sense of Cronbach's alpha. International journal of medical education 2, 53.

Thorhauge, M., Rich, J., Mabit, S.E., 2024. Charging behaviour and range anxiety in long-distance EV travel: an adaptive choice design study. Transportation 1–23. https://doi.org/10.1007/s11116-024-10561-x.

Vermunt, J., 2010. Latent class modeling with covariates: two improved three-step approaches. Polit. Anal. 18 (4), 450–469. https://doi.org/10.1093/pan/mpq025.

Vermunt, J.K., Magidson, J., 2013. Technical Guide for Latent GOLD 5.0: Basic, Advanced, and Syntax. Statistical Innovations Inc., Belmont, MA.

Wang, Y., Yao, E., Pan, L., 2021. Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. J. Cleaner Product. 286, 124982. https://doi.org/10.1016/j.jclepro.2020.124982.

Wangsness, P.B., Halse, A.H., 2021. The impact of electric vehicle density on local grid costs: Empirical evidence from Norway. Energy J. 42 (5), 149–168.

Werner, D., Paarmann, S., Wetzel, T., 2021. Calendar aging of li-ion cells—experimental investigation and empirical correlation. Batteries 7 (2), 28. https://doi.org/10.3390/batteries7020028.

Weyer, J., 1997. Konturen einer netzwerktheoretischen Techniksoziologie. In: Kirchner, U., Riedl, L., Schmidt, J.F.K. (Eds.), Technik, Die Gesellschaft Schafft: Soziale Netzwerke Als Ort Der Technikgenese. Edition Sigma, Berlin, pp. 23–52.

Wilms, R., Mäthner, E., Winnen, L., Lanwehr, R., 2021. Omitted variable bias: a threat to estimating causal relationships. Methods Psychol. 5, 100075. https://doi.org/10.1016/j.metip.2021.100075.

Winther, T., Sundet, Ø., 2023. Flexibility for whom? Householder and stakeholder perspectives on justice regarding the introduction of dynamic grid tariffs in Norway. Energy Efficiency 16 (7), 75.

Wolbertus, R., Kroesen, M., van den Hoed, R., Chorus, C.G., 2018. Fully charged: an empirical study into the factors that influence connection times at EV-charging stations. Energy Policy 123, 1–7. https://doi.org/10.1016/j.enpol.2018.08.030.

Yang, Y., Yao, E., Yang, Z., Zhang, R., 2016. Modeling the charging and route choice behavior of BEV drivers. Transport. Res. Part C: Emerg. Technol. 65, 190–204. https://doi.org/10.1016/j.trc.2015.09.008.