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Understanding drivers' willingness to incorporate V2G technology into their mobility routines

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ABSTRACT

Vehicle-to-grid (V2G) technology allows electric vehicle (EV) to not only charge but also discharge electricity back to the grid, providing benefits for the energy system and financial incentives for users. However, unlocking V2G's potential and ensuring reliable contributions to grid stability requires understanding people's willingness to participate in V2G in their daily routines, as well as the behavioural drivers and their relative importance. This study investigates individuals' willingness to plug in their private V2G-enabled EVs at each parking opportunity, adopting a flexible, daily routine-based perspective that reflects the trade-offs people make between the benefits gained and the inconveniences encountered in everyday life. In addition, recognising that plug-in behaviour involves both charging and discharging, we incorporate a range of factors that capture such complexity. A stated choice experiment was conducted in the Netherlands, where respondents made choices on whether to plug in their EVs in hypothetical scenarios. By combining stated choice experiments with latent class modelling, the study reveals heterogeneity in V2G willingness, thereby advancing current understanding and informing both energy system design and policy. Two distinct user segments are found: (1) cautious adopters, often women and non-EV owners, highly sensitive to inconvenience and battery-related concerns; and (2) confident EV pragmatists, primarily men and current EV users, showing greater tolerance for trade-offs. Policy implications are proposed in three areas: business model development, class-specific strategies and infrastructure planning. These insights contribute to enabling broader V2G adoption and integrating EVs more effectively into sustainable energy systems.

1. Introduction

Vehicle-to-grid (V2G) technology enables electric vehicles (EVs) to store excess renewable energy during periods of low demand and feed electricity back to the grid during peak demand. By doing so, V2G can enhance grid flexibility, reduce the need for infrastructure expansion, and support a more efficient and resilient low-carbon energy system (Kempton & Tomić, 2005; Van Heuveln et al., 2021; Sturmberg et al., 2024). In addition to system-level benefits, V2G can offer value to EV users through cost savings and new revenue opportunities, while supporting broader goals such as equitable access to electric mobility and the development of innovative energy service models (Niesten & Alkemade, 2016; Kubli, 2022). Unlocking the full potential of V2G requires careful design, operation, and management of the integration between the inherently complex mobility and energy systems. From the perspective of city

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planners, how to design and operationalise V2G charging infrastructure remains uncertain. Given the substantial costs and long-term investments involved, addressing these challenges is essential to ensure the viability and sustainability of V2G systems. A key element in this process is understanding user behaviour, which is critical for designing systems that meet users' needs and secure long-term acceptance.

However, most existing V2G research studying users' behaviour has focused on vehicle purchasing (Noel et al., 2019; Maeng et al., 2020) and rental decisions (Gschwendtner & Krauss, 2022), or on contractual arrangements (Bailey & Axsen, 2015; Huang et al., 2021). These studies primarily address decisions made before EV owners begin to engage with V2G in their daily lives and therefore do not fully capture the daily V2G participation, specifically, the plug-in decisions that occur in everyday routines. Research specifically addressing individual plug-in decisions in daily routines has primarily focused on charging behaviour driven by conventional EV usage needs. Studies examining plug-in behaviours under the V2G technology context remain limited (Kubli, 2022). In the V2G context, plug-in behaviour is shaped by both the desire to participate in V2G activities and the practical need to recharge, requiring an integrated understanding of both motivations.

This paper addresses this gap by analysing people's willingness to participate in V2G through their everyday plug-in behaviour. The aim is to understand when, where, and why people choose to plug-in their vehicles, thereby ensuring a consistent supply of stored energy that can make a difference to the Distribution System Operators (DSOs). Studying user behaviour provides valuable insights into the availability, timing, and amount of energy that can be supplied to the grid.

Incentive structures and business models also play a crucial role in shaping these behaviours. Most existing models rely on fixed-term contracts offering monthly or yearly remuneration but imposing rigid requirements on users' behaviour. These contractual arrangements have been one of the predominant focus of V2G-related research. However, Parsons et al. (2014) found that contract terms requiring specific plug-in times and durations were perceived as highly inconvenient by users. Eliminating such rigid conditions and adopting a more flexible model could enhance the appeal of V2G participation. Similarly, Noel et al. (2019) suggest that future V2G schemes may not require the users to sign burdensome individual contracts and instead rely on aggregated resources and forecasts, with benefits communicated directly to participants. In light of these considerations, this study does not study long-term, contract-based V2G models. Instead, it focuses on individuals' plug-in behaviour and the expected benefits of utilising current V2G opportunities at specific times and locations within their daily routines.

Ensuring broad V2G adoption requires attention to social equity. EV ownership and thus access to V2G, is currently concentrated among higher-income groups, while high purchase costs limit wider adoption (Christidis & Focas, 2019). However, the cost savings enabled by V2G may improve affordability and expand access over time. This study goes beyond previous V2G willingness and EV charging behaviour research, which has largely focused on existing EV drivers. It explicitly includes potential future EV users from diverse socio-demographic backgrounds, including lower-income groups, thereby promoting a more inclusive and equitable perspective on participation in V2G systems and electric mobility.

The paper, therefore, aims to answer the following main research questions: (1) What are the main factors that influence individuals' plug-in behaviour in their daily routines, and to what extent do these factors affect their decisions? (2) How do socio-demographic characteristics shape individuals' willingness to plug-in their EVs in their daily mobility routines? (3) How can V2G programmes be designed to encourage broad and inclusive participation across different user groups? To address these questions, we developed a web-based stated choice (SC) experiment asking if respondents would plug-in or not their EV when doing some activities during the day. We analysed the data and estimated several choice models to capture heterogeneity in preferences and behaviours. The behavioural insights derived from this research can support broader V2G adoption and offer valuable input for the planning and operational design of V2G systems.

The remainder of this paper is structured as follows: Section 2 reviews existing research on willingness to participate in V2G and examines the factors influencing conventional EV charging behaviour. Section 3 describes the stated choice experiment, including the survey design and data collection methods. Section 4 outlines the model structures used for data analysis. Section 5 presents and interprets the model estimation results. Section 6 discusses the policy implications. Finally, Section 7 concludes the paper and offers recommendations for future research.

2. Literature review

In this section, we first review existing research on people's willingness to participate in V2G. We then broaden the scope to conventional EV recharging scenarios, focusing on motivations driven only by charging needs. Together, these perspectives provide a more realistic basis for analysing plug-in behaviour in the V2G context and offer a comprehensive understanding of the factors influencing user decisions.

2.1. Research on people's willingness to participate in V2G

In the existing literature, willingness to participate in V2G has typically been studied from three main perspectives: EV purchasing or rental decisions, V2G contractual arrangements, and individual plug-in event decisions. These perspectives capture decision-making processes at different time scales: long term adoption decisions, medium term contractual commitments, and short term, day-to-day behavioural choice, respectively. Together, they offer insights into users' expectations, constraints, and incentives related to V2G participation.

While each perspective addresses some common V2G-related features, they emphasise distinct aspects of user behaviour. This section reviews these three strands to identify key gaps in the literature and the behavioural attributes that collectively inform the conceptual framework of this paper. Table 1 provides an overview of recent studies across the three perspectives, outlining the key attributes analysed and the modelling approaches used. Although socio-demographic variables are crucial for understanding user behaviour, they are not included in the table for brevity.

2.1.1. EV purchasing or rental decisions

A substantial body of research examines willingness to participate in V2G through EV purchasing or rental decisions, treating V2G-equipped vehicles as a distinct alternative compared to conventional EVs or internal combustion engine (ICE) vehicles. Some studies present V2G as a feature in broad terms by simply comparing vehicles with and without V2G capability. For example, Noel et al. (2019) describe the potential benefits and costs of V2G and model V2G capability as a binary attribute, finding that it significantly increases consumers' willingness to pay for EVs in Finland and Norway. Other studies emphasise additional functional benefits of V2G. Philip et al. (2023) show that V2G functionalities substantially increase consumers' willingness to purchase an EV, with respondents exhibiting particularly high willingness to pay for energy export to the home and/or the grid.

Beyond V2G functionality, several studies focus on specific operational attributes. Across this literature, potential cost savings and financial incentives from charging and discharging consistently emerge as important drivers of preference (Parsons et al., 2014; Hidrue & Parsons, 2015; Gschwendtner & Krauss, 2022; Philip et al., 2023). Battery-related attributes, especially minimum guaranteed driving range and limits on battery capacity available for grid exchange, also significantly influence adoption decisions (Hidrue & Parsons, 2015; Maeng et al., 2020). Some studies further incorporate behavioural constraints, such as required plug-in duration (Parsons et al., 2014; Hidrue & Parsons, 2015). But these are typically evaluated as fixed conditions attached to vehicle ownership rather than as situational choices made during daily use. In addition to V2G-specific attributes, more general EV characteristics, such as purchase price, charging time, and accessibility of charging infrastructure, jointly shape willingness to purchase or rent V2G-enabled vehicles.

Overall, this body of research provides valuable insights into users' expectations and concerns prior to adopting V2G. However, by framing V2G participation as a long-term commitment embedded in vehicle choice, these studies offer limited insight into how users respond to varying levels of inconvenience and contextual factors in their daily routines.

2.1.2. V2G contractual arrangements

Preferences for V2G contracts form another major strand of the literature, focusing on how predefined participation conditions and remuneration schemes affect users' willingness to engage in V2G. Existing studies typically distinguish between fixed and flexible contract designs. Fixed contracts offer predictable benefits, such as one-time payments or fixed monthly or annual compensation, independent of when or where users plug in their vehicles. In return, these contracts often impose strict behavioural requirements, including minimum daily plug-in hours or minimum participation frequency (Bailey & Axsen, 2015; Bakhuis et al., 2025; Yun et al., 2025).

Flexible contracts, by contrast, link remuneration more directly to actual behaviour, such as realised plug-in duration or the amount of energy returned to the grid (Huang et al., 2021). This approach reduces rigid commitments and better accommodates variability in daily travel patterns, but it also introduces greater uncertainty in expected income. Across both contract types, several attributes

Table 1
Previous studies on individuals' willingness to participate in V2G.

Author (year)	Key attributes	Modelling approach
EV purchasing/rental preference		
Parsons et al. (2014)	Price relative to gasoline vehicles; annual cash back payment; fuel cost; minimum guaranteed driving range; required plug-in time; full driving range; charging time; acceleration relative to gasoline vehicles; pollution relative to gasoline vehicles	Latent class logit model
Hidrue and Parsons (2015)	Purchase price; annual cash back; minimum guaranteed driving range; required plug-in time; availability of range extender; vehicle model; full driving range, etc	Binary logit and latent class logit models
Noel et al. (2019)	Purchase price; fuel type; full driving range; recharging time; acceleration; V2G-capablility	Mixed logit model
Maeng et al. (2020)	Purchase price; fuel cost; fuel type; electricity generation mix; battery allowance for V2G; accessibility of fuelling/charging facilities	Multiple discrete–continuous extreme value model
Gschwendtner and Krauss (2022)	Rental cost; remuneration; minimum range; carsharing scheme; access time; egress time	Multinomial logit and mixed-logit model
Philip et al. (2023)	Purchase price; driving range; financial incentives; fast charging time; public fast charger availability; V2G capabilities	Mixed logit model
V2G contractual arrangements		
Bailey and Axsen (2015)	Monthly electricity bill; guaranteed minimum charge; percentage of green electricity; source of green electricity	Latent class logit model
Geske and Schumann (2018)	One-time payments; monthly remuneration; minimum range; mandatory plugin days and hours; with or without board computer	Latent class logit model
Huang et al. (2021)	Fixed monthly remuneration; extra remuneration; guaranteed minimum battery level; average daily plug-in time; contract duration; discharging cycles	Multinomial logit model
Yun et al. (2025)	Monthly remuneration; guaranteed SOC; minimum connection days; weekday connection time; V2G charger accessibility	Latent class logit model
Individual plug-in events		
Kubli (2022)	Charging costs; guaranteed range after 50% of the charging duration; charging duration; charging location	Latent class logit model

consistently emerge as influential, including the level and structure of financial incentives, minimum guaranteed battery levels, required plug-in duration, or limits on discharging cycles. These attributes reflect users' concerns about compensation adequacy, battery security, and loss of behavioural autonomy, and thus provide useful insights for understanding daily V2G participation.

However, because contractual arrangements are defined prior to daily vehicle use, this literature does not capture situational trade-offs made in everyday routines, such as responses to varying levels of inconvenience, location, or real-time mobility needs. This limitation highlights the need for a plug-in–level analysis that treats V2G participation as a repeated, context-dependent choice rather than a contractual obligation.

2.1.3. *Individual plug-in events*

In contrast to purchase and contract studies, relatively few contributions examine plug-in behaviour during daily routines, the point at which V2G participation actually occurs. Kubli (2022) investigates individuals' preferred charging options in their daily life in the context of smart charging technologies, including V2G and vehicle-to-X. The study considers elements such as current location, charging mode, cost, and charging duration. Findings suggest that less attractive charging options can be offset by lower costs, shorter charging durations, or more convenient locations. Among locations, home charging is clearly preferred over workplace or public alternatives.

Plug-in decisions in the V2G context are strongly shaped by practical, day-to-day factors that align with individuals' activity schedules. Users weigh the potential benefits of V2G participation against the effort or inconvenience it entails before making their decisions. However, everyday inconveniences remain largely overlooked in the existing V2G literature. Incorporating daily routine factors into plug-in decision-making therefore requires attention to both temporal and spatial aspects, such as time of day, expected parking duration, charging location, and charger availability, which directly affect the potential benefits of participation. Real-time vehicle conditions at each stop, including the current state of charge (SOC) and the distance of the next trip, also play a critical role, especially when combined with range anxiety. Additional sources of inconvenience, such as walking distance to the destination and waiting time for an available charger, further shape willingness to plug in.

However, these immediate, real-world influences remain largely underexplored in the existing literature. Most prior research overlooks such contextual factors, despite their importance for understanding plug-in behaviour in the V2G context. Addressing these factors is essential for accurately predicting participation rates and represents a significant gap in current V2G research.

2.2. *EV charging behaviour analysis*

Plug-in behaviour in V2G context is influenced by both recharging needs and V2G-related factors. However, most existing V2G studies focus primarily on the discharging aspect, ignoring how recharging needs fundamentally drive plug-in decisions. To better understand plug-in behaviour under a V2G context, it is therefore relevant to review insights from the broader EV charging literature. Table 2 summarises the recent studies on EVs' charging behaviours, however providing a comprehensive review of all existing gaps in EV charging research is not the aim of this paper. We aim to highlight the main drivers of plug-in behaviour motivated by recharging needs. Readers interested in such topics may consult detailed literature reviews such as (Liao et al., 2017; Solvi Hoen et al., 2023).

Existing studies typically explore choices such as whether to plug-in the EV or not (Pan et al., 2019; Wang et al., 2021), selection among multiple charging stations or locations (Zhao et al., 2020; Brückmann & Bernauer, 2023; Solvi Hoen et al., 2023; Sica et al., 2025), route choices combined with charging behaviour (Ashkrof et al., 2020), or the type of charging that they prefer (Daina et al., 2017; Yang et al., 2024). According to these studies, the factors most significantly influencing EV charging behaviour typically fall into the following main categories.

The first set of factors relates to service attributes, including charging time (Zhao et al., 2020; Brückmann & Bernauer, 2023; Solvi Hoen et al., 2023; Yang et al., 2024; Sica et al., 2025), charging type, fast or slow charging (Neaimeh et al., 2017; Pan et al., 2019; Solvi

Table 2
Previous studies on EVs charging behaviour.

Authors (year)	Key attributes	Modelling approach
Daina et al. (2017)	Target energy after charging, charging time, charging cost.	Binary logit, mixed logit models
Pan et al. (2019)	SOC; EV remaining range; excess range; distance to the next destination; charging cost; parking price; location; dwell time; charging type	Binary logit, hybrid choice, fully compensatory latent class, and attribute non-attendance latent class models
Zhao et al. (2020)	Distance between the charging point and the destination; charging cost; charging time; accessibility of piles; safety	Binary logit model
Wang et al. (2021)	SOC; excess range; charging cost; parking time; queueing time; satisfaction	Binary logit and latent class logit models
Zhang et al. (2022)	SOC; travel distance of next trip; charging cost; location; parking time	Hybrid choice model
Brückmann and Bernauer (2023)	Charging cost; charging time; queueing time; surrounding amenities; energy source	Binary logit model
Solvi Hoen et al. (2023)	SOC; battery level after; range left after; distance to destination; charging cost; waiting time for free charge; charging time; charger type; facilities	Mixed logit model
Yang et al. (2024)	Charging station distance; charging cost; charging time; waiting time before charging; charging time slot	Latent class logit model
Sica et al. (2025)	Charging cost; charging time; waiting time; charging station typology; comfort and ancillary services; energy from renewable sources, connection technology; possibility of booking	Multinomial logit and nested logit models

Hoen et al., 2023), waiting time before charging (Brückmann & Bernauer, 2023; Solvi Hoen et al., 2023; Yang et al., 2024; Sica et al., 2025), location (Zhang et al., 2022; Solvi Hoen et al., 2023), cost (Pan et al., 2019; Zhao et al., 2020; Wang et al., 2021; Zhang et al., 2022; Brückmann & Bernauer, 2023; Solvi Hoen et al., 2023; Yang et al., 2024; Sica et al., 2025), and accessibility. The second set of factors reflects range-related concerns, SOC (Pan et al., 2019; Wang et al., 2021; Zhang et al., 2022; Solvi Hoen et al., 2023), remaining driving range (Pan et al., 2019; Wang et al., 2021; Solvi Hoen et al., 2023), and the distance of the next planned trip (Pan et al., 2019; Zhang et al., 2022). These connect to the well-documented phenomenon of range anxiety, where uncertainty about remaining driving capacity strongly shapes charging choices (Franke & Krems, 2013). Third, socio-demographic factors influence preferences (Plötz et al., 2014; Hardman & Tal, 2016). Differences in income, gender, or EV ownership status affect tolerance for inconvenience, willingness to pay, and adoption of new charging practices.

While these insights are directly relevant for understanding plug-in behaviour, most EV charging studies do not account for the additional incentives and trade-offs introduced by V2G participation. As a result, existing EV charging research provides an essential foundation but does not fully explain how users balance recharging needs and V2G-related benefits within daily routines. Building on these insights, this study explicitly focuses on behavioural and situational factors influencing plug-in decisions in a V2G context, including SOC, parking location, expected waiting time, walking distance to the destination, and the distance of the next planned trip. By linking both the willingness to charge and discharge, our approach addresses an underexplored dimension of plug-in behaviour that existing research has yet to fully capture.

Considering the above discussion, the key contributions of this paper are threefold:

- Unlike previous studies that mainly examine directly contract-based V2G models with rigid behavioural constraints, this study introduces a flexible, routine-aligned perspective that integrates both the charging needs and the willingness to participate in V2G at each parking opportunity, which can support better future schemes for the travellers.
- It goes beyond existing work on EV charging behaviour by explicitly focusing on the behavioural dynamics of plug-in decisions under the V2G context, thereby filling a gap between conventional charging research and V2G adoption studies.
- By including not only current EV owners but also potential future users from diverse socio-demographic groups, the study advances a more inclusive understanding of V2G's large-scale adoption potential and its equity implications.

3. Stated choice experiment

3.1. Survey design

In discrete choice modelling applications, parameters can be estimated using either stated choice (SC) or revealed preference (RP) data. However, since V2G technology is not yet widely available in the market, collecting RP data is currently not feasible. Therefore, this study relies on SC data, gathered by presenting respondents with hypothetical scenarios that include a range of attributes and levels, from which they are asked to make choices for whether or not they would plug in their V2G-equipped EV. Besides the stated choices, socio-demographic information is collected as well.

To familiarise respondents with V2G technology, the survey begins with a clear and easy-to-understand introduction, accompanied by an animated illustration. This introduction outlines both the opportunities and challenges associated with V2G, helping participants understand the potential benefits and drawbacks they may encounter during real-world use. Given that most respondents may not have direct experience with V2G, the introductory material serves to provide a common baseline of knowledge. At the same time, we recognise that participants' evaluations may still be influenced by their limited real-world experience with the technology despite this preparation. The full introduction is provided in Appendix A.

After this, respondents are asked to imagine that they own an EV equipped with V2G capabilities and hold a valid driving licence to use it. The following contextual information is then presented to them:

> *"Imagine a typical weekday when you use your electric vehicle (EV) equipped with this Vehicle-to-grid (V2G) technology. When you drive to places like work or shopping areas or return home for the night, you might have a chance to plug in your vehicle at a V2G charging station. Six different scenarios will be presented, and you will need to decide whether to plug in your vehicle or not."*

Table 3
Level of attributes.

Attribute	Attribute Levels
Location	Home, workplace, shopping area
Parking time	Home and workplace: 2, 4, 8 h Shopping area: 1, 2, 4 h
Distance of next trip	5, 25, 50, 80 km
SOC	10%, 30%, 60%, 90% (30 km, 90 km, 180 km, 270 km)
Daily electricity cost savings from the current plug-in behaviour	0, 2, 6, 10 euro/day
Minimum guaranteed battery range	20%, 40%, 60% (60 km, 120 km, 180 km)
Walking time from your location to a V2G station	0, 5, 10 mins
Waiting time for a charging slot	0, 5, 10 mins
Number of (partial) discharging circles	0, 3, 6

Respondents were then presented with six choice tasks, each defined by nine attributes and their corresponding levels. These attributes and their levels were selected based on the review of the literature. An overview of the attributes and levels is provided in Table 3.

Location has been shown to significantly influence EV charging behaviour. In this study, we use three specific locations, home, workplace, and shopping area, to present respondents with realistic options that reflect their typical daily routines (Pan et al., 2019; Kubli, 2022). The "home" location does not necessarily imply the presence of a private charger; rather, it may also refer to nearby public charging facilities within the residential area. In this sense, charging near home can involve some walking or waiting time. The time dimension is implicitly embedded in these location choices: (near-) home charging typically occurs in the evening or overnight, while workplace charging usually takes place during the daytime.

Parking durations differ across locations, with home and workplace charging typically involving longer stays compared to shopping areas, based on common daily routines. Therefore, we set the attribute levels for parking time at home and work to 2, 4, and 8 h, and at shopping areas to 1, 2, and 4 h (Pan et al., 2019). Longer parking durations increase the likelihood that plug-in periods coincide with economically optimal charging or discharging windows.

Cost saving is a commonly used attribute in studies examining individuals' willingness to participate in V2G. Such savings can arise from both charging and discharging activities. For instance, EVs can be charged at a lower cost during periods of surplus renewable energy and later discharge electricity to the grid during peak demand, thereby generating additional value. Although this study focuses on individual plug-in events, discharging may not necessarily occur during every plug-in session; some sessions may involve only charging. Presenting session-specific charging cost or discharging cost savings could lead respondents to focus primarily on revenue-generating discharging events and to plug in only when discharging is possible, without accounting for the required charging process. Therefore, we consider the cost savings from a broader, daily perspective, accounting for the potential aggregate benefit resulting from the current plug-in behaviour. We refer to this attribute as the *expected daily electricity cost savings* resulting from the current plug-in behaviour. The levels are set at 0, 2, 6, and 10 euros per day.

When cost savings act as an incentive, individuals must balance the financial benefits against potential inconveniences. One such inconvenience is that the charging station may not be located directly at the desired destination, which requires EV owners to park at the charging point and walk the remaining distance. In this study, we use 0, 5, and 10 min as the attribute levels for walking time to a V2G charging station. Another source of discomfort may arise when public charging spots are occupied upon arrival, requiring users to wait until a charger becomes available. The levels for this waiting time attribute are also set at 0 (no delay), 5, and 10 min.

Range anxiety is a well-established driver of conventional EV plug-in behaviour. Even if the anxiety tends to dissipate as batteries have more capacity, with V2G, we add consumption at the bidirectional charging station, which can bring back the problem. Such anxiety can be assessed through indicators such as the *vehicle's current SOC* and *the distance of the next trip*, which together determine whether the available range is sufficient for upcoming travel needs. In this study, we set the levels of the distance that will need to be covered in the next trip at 5, 25, 50, and 80 km. The SOC levels are set at 10%, 30%, 60%, and 90%, corresponding to approximately 30 km, 90 km, 180 km, and 270 km of driving range, based on an assumed full battery range of 300 km.

In the context of V2G, an additional consideration becomes important: the *minimum guaranteed battery range* after charging and discharging cycles. When an EV is plugged in, the system ensures that the battery is charged to meet a minimum required range for the driver's next trip. To protect battery health, this guaranteed range is typically maintained within a safe SOC window, generally between 20% and 80–90%, to avoid deep discharging or charging to full capacity, both of which can accelerate battery degradation (Wei et al., 2022). To capture post-plug-in range anxiety, we include the attribute *minimum guaranteed battery range*, with levels set at 20%, 40%, and 60%, equivalent to 60 km, 120 km, and 180 km, respectively. This ensures that respondents consider whether the remaining range after participating in V2G is sufficient for their needs.

Battery degradation remains one of the primary concerns for EV owners (Van Heuveln et al., 2021). To date, the impact of charging

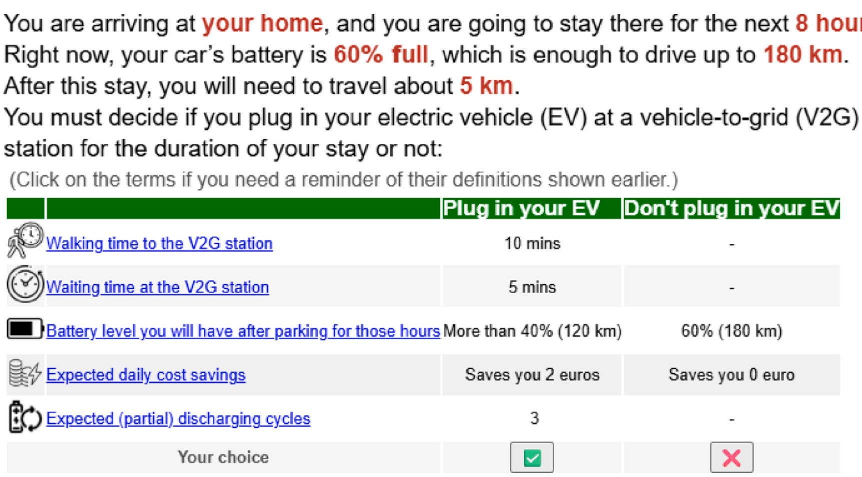
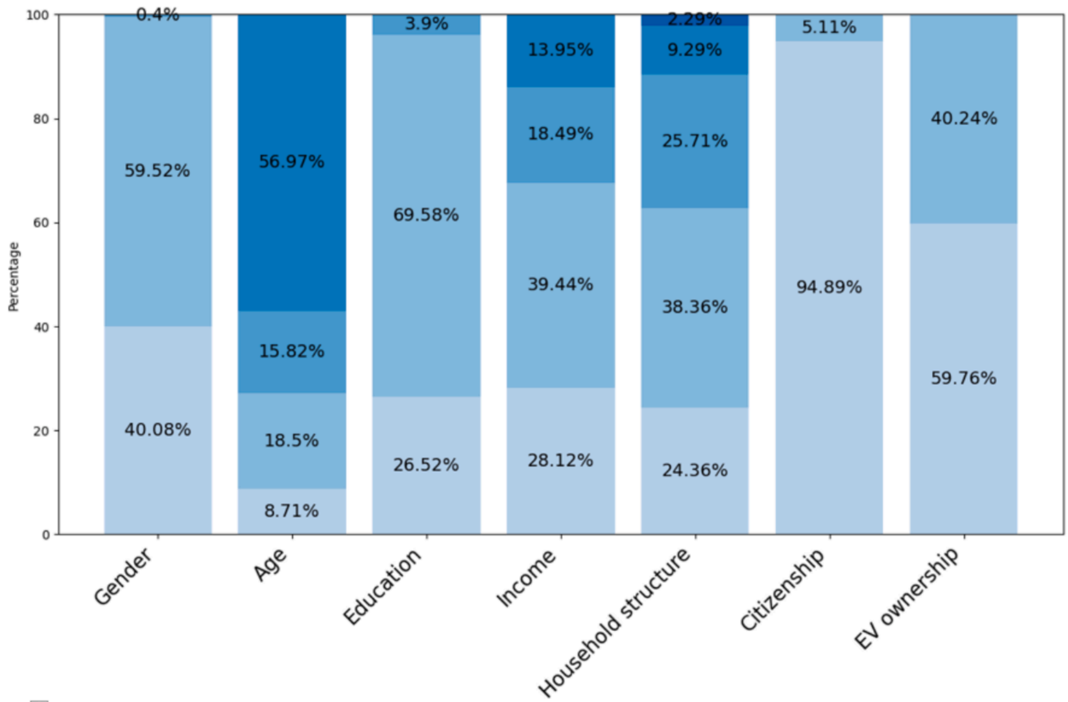


Fig. 1. Example of a choice task in the experiment.

and discharging cycles on battery health remains a topic of debate. Some studies suggest that V2G has the potential to improve battery longevity (Uddin et al., 2018), while others argue that frequent charging and discharging may accelerate battery degradation (Parsons et al., 2014). Given this uncertainty, it is difficult to quantify the precise effect of battery degradation on a daily basis. To capture respondents' attitudes toward this issue, we include an attribute representing battery usage intensity, with levels set at 0, 3, and 6 discharging cycles per session corresponding to no discharging, moderate, and high perceived impacts on battery health (Huang et al., 2021).

The choice tasks for the SC experiment were generated using Ngene employing a D-efficient design. To ensure the logical consistency and realism of each choice task, several constraints were applied during the design process: (1) If the discharging cycle is 0, indicating no discharging activity, the minimum battery range after plug-in must not be lower than the SOC before plug-in; (2) If the daily cost saving from the current plug-in behaviour is 0, meaning that the plug-in behaviour at that time and location offers no financial benefit, then no discharging should occur, and the minimum battery guarantee after plug-in must be greater than or equal to the initial SOC; (3) Both the SOC before plug-in and the minimum guaranteed battery range after plug-in should be sufficient to cover the distance of the next trip, to avoid scenarios where respondents would be forced to plug in their EVs without having to make trade-offs between the presented attributes. In total, 36 choice tasks were generated, with each respondent being assigned a subset of 6 tasks. An example of a choice task can be seen in Fig. 1.

After the stated choice experiment, socio-demographical data were collected on the following characteristics: gender, age, education level, household structure, income level, citizenship status, access to private and public transport. For respondents who own an EV, additional questions were asked regarding their minimum SOC before charging and their preferred minimum guaranteed battery range, to better understand their individual charging preferences and expectations related to driving range.



Legend					
Gender	Female	Male	Other		
Age	18-24	25-34	35-44	45 or older	
Education	No higher education	With higher education	Prefer not to say		
Household income per month (euro)	Low (≤3000)	Middle (> 3000 and ≤6000)	High (>6000)	Prefer not to say	
Household structure	I live alone	With partner, no kids	With partner and kids	Shared flat with family or friends	Prefer not to say
Citizenship	Dutch citizen	Other			
EV ownership	Without EVs	With EVs			

Fig. 2. Full sample composition.

3.2. Data collection and descriptive statistics/sample characteristics

The survey was designed using the online platform Qualtrics and distributed in the Netherlands via anonymous links and QR codes. It was available in both English and Dutch to accommodate a wide range of respondents in the Netherlands. The study did not require respondents to hold a valid driving licence, as the objective was to capture both current and potential future users of V2G technology. However, all participants were required to be at least 18 years old.

Data were collected through three main channels: (1) On-street distribution (6.14%) in the district of Kanaleneiland, a neighbourhood in Utrecht in the Netherlands, characterised by a multicultural population with a high proportion of social housing and low-income households. The district, actively involved in sustainable urban initiatives, provides a valuable setting for studying V2G adoption among lower-income communities; (2) Collaboration with panel companies (67.23%) to reach a broader sample in the country, and (3) Partnership with the Dutch Association of EV Drivers (26.63%) to involve more EV owners in the experiment since panel companies do not.

The responses were collected between February and April 2025. To ensure data quality, we first excluded all incomplete responses, and those completed in less than five minutes in order to remove speeders. After this cleaning process, a total of 741 valid responses (4446 observations) were retained for analysis. Fig. 2 shows the sample characteristics.

The sample includes a higher proportion of EV owners than the general Dutch population in order to ensure sufficient representation of individuals with direct experience of EV use and charging behaviour. At the same time, non-EV owners are also included to capture the perspectives of potential future users. The relatively high share of highly educated respondents reflects well-known challenges in reaching lower-education groups in survey-based research. To address this, we complemented the survey with on-street distribution in Kanaleneiland to better reach lower-income households. Socio-demographic characteristics are explicitly accounted for in the analysis to capture heterogeneity in preferences. As the focus of the study is on identifying behavioural patterns and trade-offs rather than predicting population-level adoption rates, the estimated coefficients remain informative despite the non-representative sample composition. In addition, previous research has shown that logit models yield unbiased parameter estimates even when the sample is not fully representative, provided that socio-demographic characteristics are included as control variables (Mo et al., 2021; Liao et al., 2024).

To understand current EV users' charging behaviour and the potential battery range that could be available for future V2G activities, we asked only to the EV current users (part of the sample) about two aspects, as they have real-life charging experience, the following: the battery level at which they typically begin charging and their preferred minimum guaranteed battery range after participating in V2G. Fig. 3 shows the distribution of their responses. Over half of the respondents reported that they usually start charging when the battery level falls between 20% and 40%. A similar pattern is observed in their preferred minimum range after V2G use, indicating that most users are comfortable using a substantial portion of the battery before recharging. Only a small share of respondents, approximately 11% and 9% in the two cases, are willing to let the battery drop below 20%, likely due to range anxiety or concerns about battery degradation. Conversely, a small group (around 10%) prefers to maintain a minimum guaranteed battery level above 60%, possibly due to longer daily travel requirements or limited access to charging infrastructure. These findings highlight the significant potential for utilising EV batteries to support grid stability, if user preferences are adequately considered in V2G system design.

Notably, the proportion of respondents preferring higher minimum ranges (40–60%, 60–80%, and above 80%) after V2G participation is greater than the proportion who prefer those same ranges for regular charging. This is logical, and it indicates that users expect a slightly higher SOC after discharging to ensure sufficient range for subsequent trips.

To understand the full sample general perspectives on EVs and V2G adoption, we asked all respondents (both current EV users and potential future users) two questions: (a) their general attitudes toward EVs, and (b) their likelihood of purchasing a V2G-equipped EV or upgrading their current EV to support V2G functionality. The results are presented in Fig. 4. As shown in Fig. 4 (a), the majority of respondents hold a positive view of EVs, with only 9% expressing a negative attitude. Regarding V2G adoption, Fig. 4 (b) shows that approximately 48% of respondents indicated a high likelihood of purchasing or upgrading to a V2G-capable EV, while only 27% reported that such a transition is unlikely for them. These findings indicate strong potential for large-scale V2G adoption, supported by generally positive attitudes toward EVs and significant interest in V2G functionalities.

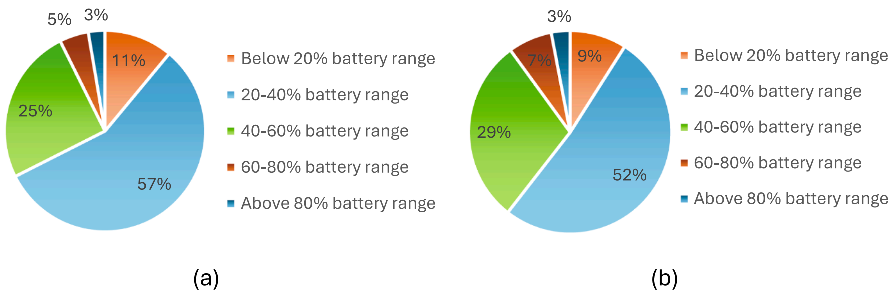


Fig. 3. (a) EV owners' preferences for minimum battery level before charging; (b) EV owners' preferences for minimum guaranteed battery range after V2G participation.

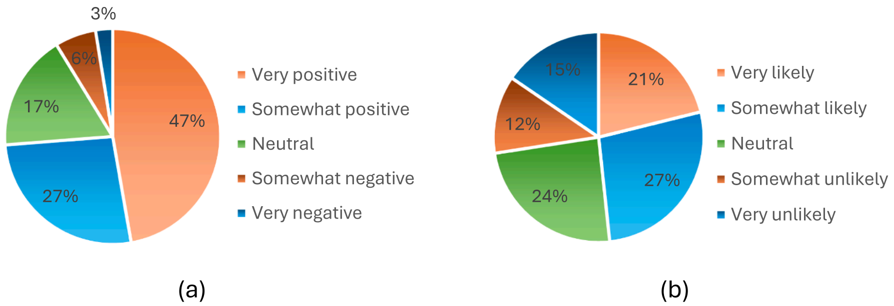


Fig. 4. (a) Respondents' general attitudes towards EVs; (b) Likelihood of purchasing a V2G-equipped EV or upgrading their current EV to support V2G.

4. Choice model structures

We begin with a binary logit (BL) model, which is appropriate given the binary nature of the decision of the plug-in decisions (plug in or not). The BL model provides a useful baseline by estimating the average influence of key attributes on plug-in behaviour across the full sample. However, plug-in preferences are unlikely to be homogeneous; rather, they are latent and shaped by socio-demographic differences (e.g., income, EV ownership, gender) as well as by varying tastes toward convenience, cost, and battery health.

In this context, the latent class logit (LCL) model is particularly suitable because it accounts for unobserved heterogeneity by identifying latent segments of users, each with distinct decision-making patterns. This segmentation is not imposed a priori but emerges from the data, making it well suited to studying an emerging and unfamiliar system such as V2G. While mixed logit models (MXL) are also commonly used in SC studies to capture the unobserved heterogeneity, they require strong distributional assumptions about random parameters. Compared to MXL, the LCL framework provides greater interpretability and policy relevance, as the estimated classes can be linked to socio-demographic profiles and used to design targeted interventions.

By analysing BL and LCL model, we first establish a baseline of general trends and then uncover hidden heterogeneity in plug-in decisions.

4.1. Binary Logit (BL) model structure

BL model is the simplest and most frequently used in the study of whether or not to plug-in EVs for charging in the literature. The model is based on random utility maximization (RUM), which assumes that individuals choose the alternative that provides the highest utility. The utility U_{ri} that an individual r derives from choosing an alternative $i \in \{0, 1\}$ is decomposed into a systematic (observable) component V_{ri} and a random (unobservable) component ε_{ri}:

$$U_{ri} = V_{ri} + \varepsilon_{ri} \tag{1}$$

The systematic utility V_{ri} is computed typically as a linear function of observed attributes $x(j)$ and its taste parameter β_j, as shown in Equation (2). The random error term ε_{ri} captures unobserved influence. Assuming that the error terms ε_{ri} are independently and identically distributed (i.i.d.) following a Gumbel distribution, the probability that an individual r chooses an alternative i is given by Equation (3)

$$V_{ri} = \sum_{j}^{x} \beta_j x_{ri}(j) \tag{2}$$

$$P_{ri} = \frac{e^{V_{ri}}}{e^{V_{r0}} + e^{V_{r1}}} \tag{3}$$

In this study, we define alternative 1 as the decision to plug in and alternative 0 as the decision not to plug in. The systematic utility V_{ri} is specified in the next section based on behavioural and socio-demographic attributes.

4.2. Latent Class Logit (LCL) model structure

LCL models estimate the class-specific sets of parameters, and the likelihood of the respondents belonging to one class given a fixed number of classes (Wen & Lai, 2010; Potoglou et al., 2020; Singh et al., 2023). The probability that a respondent r chooses alternative i, conditional on the set of parameters $\boldsymbol{\beta}$ is expressed as follows:

$$P_r(i|\boldsymbol{\beta}) = \sum_{s=1}^{S} \pi_{rs} \cdot P_r(i|\boldsymbol{\beta}_s) \tag{4}$$

where

$$\pi_{rs} = \frac{e^{\delta_s + \sum_{q=1\cdots Q} \gamma_{sq} z_{rq}}}{\sum_{l=1\cdots L} e^{\delta_l + \sum_{q=1\cdots Q} \gamma_{lq} z_{rq}}} \tag{5}$$

Here, π_{rs} represents the class membership probability, representing the likelihood that respondent r belongs to class s, depending on socio-demographic variables such as gender or income.$P_r(i|\boldsymbol{\beta}_s)$ is the probability that respondent r chooses alternative i, given that respondent r belongs to class s, and is modelled using the multinomial logit formulation. The vector $\boldsymbol{\beta}_s$ contains the class-specific taste parameters. The overall choice probability is then obtained by summing over all S latent classes.

In the class membership function (5), δ_s denotes the class-specific constant. Q represents the number of observable socio-demographic characteristics. γ_{sq} is the estimated parameter associated with characteristics q for class s, and z_{rq} denotes the variable that represents characteristics q for respondent r in the dataset. This formulation allows class membership to be systematically related to observable respondent attributes that may influence plug-in behaviour.

Considering that the data collected in this study are panel data, where each respondent completed six consecutive choice tasks regarding whether to plug in their EV or not, the model accounts for this repeated-measure structure. Specifically, the likelihood was formulated at the respondent level by taking the product of the probabilities of the six observed choices for each individual (Greene & Hensher, 2003). This ensures that the dependence between repeated observations from the same respondent is properly captured, rather than treating them as independent. The likelihood of observing the full sequence of choices for respondent r, conditional on the vector of model parameters $\boldsymbol{\beta}$, is given by:

$$L_r(i_t, \cdots, i_T|\boldsymbol{\beta}) = \sum_{s=1}^{S} \pi_{rs} \prod_{t=1}^{T} P_r(i_t|\boldsymbol{\beta}_s) \tag{6}$$

In this equation, the probability of the observed sequence of T choices is computed as the product of individual choice probabilities, given that respondent r belongs to class s. This is then weighted by the class membership probability π_{rs} and summed over all S latent classes.

The log-likelihood function of the LCL model for the sample is summation of each respondent's natural logarithm of the unconditional likelihood (Potoglou et al., 2020):

$$LL(\beta) = \sum_{r=1}^{R} ln \sum_{s=1}^{S} \pi_{rs} \prod_{t=1}^{T} P_r(i_t|\beta_s) \tag{7}$$

To determine the optimal number of latent classes, we use the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). BIC is generally preferred over AIC because it applies a stronger penalty for model complexity, helping to avoid overfitting by more heavily penalising the number of estimated parameters (Wen & Lai, 2010; Singh et al., 2023).

5. Model specification and estimation

Among all 741 valid respondents, 140 were identified as non-traders, with 94 respondents consistently choosing to plug in and 46 consistently choosing not to in all the choice tasks. In our study, respondents who always chose to plug-in or always chose not to may reflect different behaviour. These individuals could be people with extreme preferences: V2G enthusiasts, who are highly supportive of technology, or V2G sceptics, who are concerned about its potential drawbacks. They may also be individuals who did not engage seriously with the experiment. From a choice modelling perspective, such respondents do not reveal meaningful trade-offs across attributes, which can bias parameter estimates and willingness-to-pay (WTP) measures (Smith et al., 2017). Thus, we excluded them from the estimation sample, resulting in 601 valid responses and 3,606 observations.

This section presents the LCL model specifications and results based on the estimation sample without non-traders. The BL model specifications and results are reported in Appendix B for reference. As a robustness check, we also re-estimated the LCL model including non-traders; the corresponding results are provided in Appendix C.

5.1. LCL model specification and results

We firstly have specified the utility function in the LCL model with a rich set of interaction terms and socio-demographic covariates. However, in estimation, these additions did not improve model fit or lead to more meaningful class segmentation. Since the LCL model already captures preference heterogeneity primarily through between-class segmentation, introducing further within-class variation offered limited benefit while greatly increasing the number of parameters. Therefore, we adopt a more parsimonious specification in which socio-demographic variables are included only in the class-membership model. The notation used can be found in Table 4.

We keep only one exception: the interaction between income and cost saving. Income is represented by three dummy variables, *IH* (high income), *IM* (middle income), and *IL* (low income). Each interacts with the cost-saving variable *CS*. These interaction terms are statistically significant and capture meaningful differences in cost sensitivity across respondents within the same class.

Income alone was not a significant determinant of class membership. Including these interactions in the utility function thus provides valuable behavioural insights without over-parameterising the model. The resulting utility functions for the plug-in alternative are expressed as:

$$V_{r1}^{LCL} = \beta_0 + \beta_{LW} \cdot LW + \beta_{LS} \cdot LS + \beta_{PT} \cdot PT + \beta_{DT} \cdot DT + \beta_{CS\times IH} \cdot CS \cdot IH + \beta_{CS\times IM} \cdot CS \cdot IM + + \beta_{CS\times IL} \cdot CS \cdot IL + \beta_{WKT} \cdot WKT + \beta_{WTT} \cdot WTT + \beta_C \cdot C + \beta_{SOC} \cdot SOC + \beta_{BG} \cdot BG \tag{8}$$

Before estimating the LCL models, the first step is to determine the best number of classes. To do this, we perform an iterative estimation procedure, testing models with between 1 and 5 classes. The case with 1 class corresponds to the BL model, which is included here for comparison purposes. Model selection is based on the BIC, AIC, and the interpretability of the resulting class structure. The corresponding BIC and AIC values for each model specification are presented in Fig. 5.

From Fig. 5, it can be observed that the BIC value decreases from the 1-class to the 3-class model, then increases as the number of classes continues to grow. This is due to the increasing number of parameters, which adds to model complexity. In contrast, the AIC value continues to decrease from the 1-class to the 5-class model. Both indicators show significant improvement in model fit when moving from the BL model to the LCL model. Considering the trade-off between model fit and complexity, the 2-class and 3-class models are preferred. Upon comparing the estimation results, the 2-class model yields clearer and more interpretable segmentation than 3-class models. Similar conclusions were drawn after incorporating socio-demographic variables into the class membership functions of the LCL model. Therefore, the 2-class model is selected for further analysis.

5.2. Estimation results

Table 5 presents the results of the LCL model, which divides respondents into two distinct classes based on their behavioural responses and socio-demographic profiles. All parameters are retained, regardless of significance, to ensure consistent class comparisons and to provide behavioural insights. As noted by Hess et al. (2025), retaining parameters with reported p-values improves transparency and clarifies modelling limitations.

5.2.1. Class membership and alternative-specific constants

The class membership model indicates that gender and EV ownership are key determinants of latent class assignment. In particular, Class 1 is significantly associated with EV ownership and male respondents, as reflected by a positive coefficient for EV ownership (0.612) and a negative coefficient for women (–0.804). A positive class-specific constant (0.744) further suggests that respondents exhibit a higher baseline probability of belonging to Class 1 even after accounting for observed socio-demographic characteristics. This indicates the presence of unobserved factors, such as familiarity with EV technology or greater confidence in new energy services, that systematically increase the likelihood of belonging to this class.

In contrast, Class 0 is more likely to include women and non-EV owners, suggesting a segment characterised by lower familiarity with EV and V2G technologies and greater perceived uncertainty. This segmentation aligns with prior findings showing that EV ownership and familiarity towards V2G play an important role in shaping acceptance and participation decisions (Gschwendtner & Krauss, 2022). Gender differences observed here are also consistent with earlier research indicating that men tend to exhibit higher willingness to adopt EVs and V2G technologies, potentially reflecting differences in risk perception, technological confidence, and interest in automotive innovations (Parsons et al., 2014; Sovacool et al., 2018).

To better visualise how class membership probabilities vary across gender and EV ownership, we calculate the probabilities using Equation (5) and present the results in Fig. 6.

Table 4
Descriptions of parameters and variables.

Parameter	Description	Variable	Description
β_0	Alternative-specific constant, general preference for plugging in		
β_{LW}	Parameter for workplace location relative to home	LW	Dummy variable = 1 if location is workplace, 0 otherwise
β_{LS}	Parameter for shopping area location relative to home	LS	Dummy variable = 1 if location is shopping area, 0 otherwise
β_{PT}	Parameter for parking time	PT	Parking time
β_{DT}	Parameter for distance of the next trip	DT	Distance of the next trip
β_{CS}	Parameter for expected daily cost savings	CS	Expected daily cost savings
β_{WKT}	Parameter for walking time	WKT	Walking time
β_{WTT}	Parameter for waiting time	WTT	Waiting time
β_C	Parameter for expected number of discharging cycles	C	Expected number of discharging cycles
$\beta_{CS\times IL}$	Interaction effect between expected daily cost savings and low-income status	IL	Dummy variable = 1 if income $\leq$ €3,000, 0 otherwise
$\beta_{CS\times IH}$	Interaction effect between expected daily cost savings and high-income status	IH	Dummy variable = 1 if income > €6,000, 0 otherwise
$\beta_{CS\times IM}$	Interaction effect between expected daily cost savings and middle-income status	IM	Dummy variable = 1 if income > €3,000 and $\leq$€6,000, 0 otherwise
β_{SOC}	Parameter for current state of charge of the EV	SOC	Current state of charge of the EV
β_{BG}	Parameter for minimum guaranteed battery range	BG	Minimum guaranteed battery range

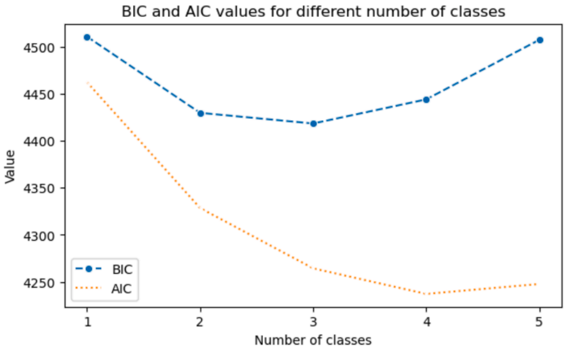


Fig. 5. BIC and AIC value for the BL and LCL models.

Table 5
Estimation results of the latent class model.

Attributes in choice tasks	Class 0: Cautious adopters Value	Std err	p-value	Class 1: Confident EV pragmatists Value	Std err	p-value
Alternative specific constant (ASC)	0.565	0.988	0.57	0.589	0.337	0.08
Minimum battery guarantee (*BG*)	0.014	0.005	0.01	0.003	0.001	0.02
Cost saving for high income ($CS \times IH$)	0.262	0.110	0.02	0.151	0.024	0.00
Cost saving for middle income ($CS \times IM$)	0.161	0.080	0.04	0.128	0.018	0.00
Cost saving for low income ($CS \times IL$)	0.242	0.140	0.08	0.141	0.034	0.00
Discharging cycles (*C*)	−0.202	0.083	0.02	−0.002	0.032	0.96
Distance of next trip (*DT*)	0.029	0.016	0.07	−0.003	0.003	0.22
Location: shopping area (*LS*)	0.680	0.939	0.47	−0.478	0.169	0.00
Location: workplace (*LW*)	−0.035	0.870	0.97	−0.274	0.265	0.30
Parking time (*PT*)	0.322	0.167	0.05	0.046	0.021	0.03
SOC (*SOC*)	−0.034	0.015	0.03	−0.002	0.002	0.31
Waiting time (*WTT*)	−0.046	0.036	0.20	−0.049	0.015	0.00
Walking time (*WKT*)	−0.149	0.066	0.02	−0.080	0.017	0.00
Class membership function						
Class intercept	–	–	–	0.744	0.368	0.04
EV ownership (1: with EVs; 0: without EVs)	–	–	–	0.612	0.292	0.04
Gender (1: women; 0: men)	–	–	–	−0.804	0.294	0.01
Estimation indicators	**Value**					
Nbr of parameters	29					
Sample size	601					
Observations	3606					
Null log likelihood	−2499.489					
Final log likelihood	−2119.292					
Likelihood ratio test (null)	760.393					
Rho square (null)	0.152					
Rho bar square (null)	0.141					
Akaike Information Criterion	4296.585					
Bayesian Information Criterion	4424.144					

Differences between the classes also emerge in the alternative-specific constants (ASCs). The positive and significant ASC for the plug-in alternative in Class 1 indicates an underlying preference to plug in that is not fully explained by observed attributes. In contrast, the absence of such a positive baseline preference in Class 0 implies that plug-in decisions for this group are more strongly related to explicit incentives and situational factors, rather than on underlying inclination to participate.

5.2.2. Cost saving sensitivity and income effects

In terms of cost savings, all income groups across both classes exhibit a significant positive sensitivity to cost savings, indicating that higher financial benefits increase the likelihood of plugging in. This finding is consistent with existing literature showing that remuneration and financial incentives positively influence V2G participation (Parsons et al., 2014; Geske & Schumann, 2018; Huang et al., 2021; Wong et al., 2023).

However, the magnitude of cost sensitivity differs markedly between the two classes, reflecting heterogeneous preferences. Class 0 exhibits stronger and more varied sensitivity to cost savings across income groups, suggesting that individuals in this class require higher levels of financial compensation to participate in V2G. In contrast, Class 1 shows consistently lower sensitivity to cost savings, with relatively small differences across income levels.

When we look at income groups more closely, middle-income respondents display the lowest sensitivity to cost savings compared with both high- and low-income groups. This suggests that middle-income individuals require larger financial incentives to engage in

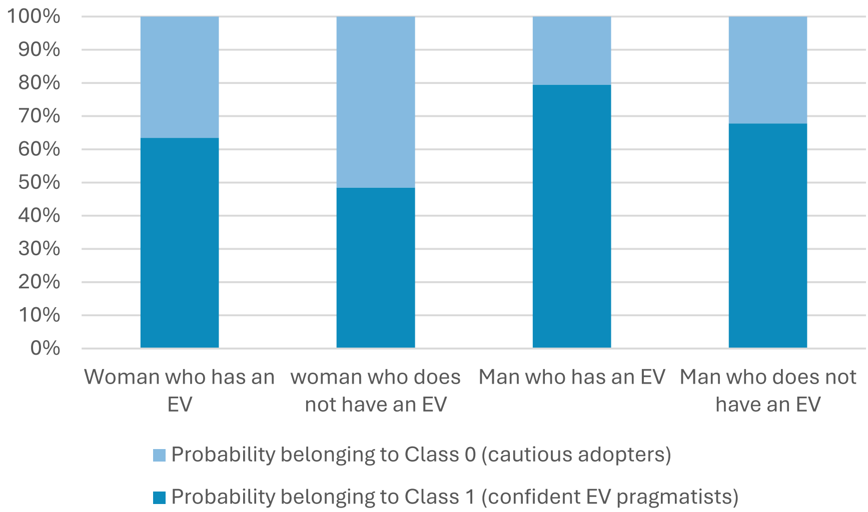


Fig. 6. Class membership probabilities across gender and EV ownership profiles.

V2G. The underlying motivations across income groups may therefore differ. High-income respondents may be more inclined to participate due to their interest in the benefits of V2G technology or broader sustainability considerations (Will & Schuller, 2016), while low-income respondents appear more responsive to direct financial benefits. By contrast, middle-income respondents may be relatively more indifferent to V2G participation compared to the other two groups. These differences in underlying motivation could be examined more explicitly by incorporating attitudinal measures. However, such questions were not included in the present study due to survey length constraints. Future research could therefore explore the psychological and attitudinal factors shaping V2G plug-in behaviour.

5.2.3. Range anxiety and battery-related concerns

Regarding range anxiety and battery-related concerns captured through the attributes of minimum guaranteed battery range, SOC, distance of the next planned trip, and number of discharging cycles, clear behavioural heterogeneity emerges between the two classes.

Both classes value a higher minimum guaranteed battery range after V2G participation, which coincides with the findings in previous studies (Parsons et al., 2014; Geske & Schumann, 2018; Huang et al., 2021); however, Class 0 places greater importance on this attribute compared to Class 1, indicating stronger risk aversion and heightened concerns about insufficient driving range.

Sensitivity to SOC is statistically significant only for Class 0. Higher SOC levels reduce the likelihood that individuals in this class will plug in and participate in V2G, indicating that their decisions are strongly driven by immediate recharging needs and reflect a more risk-averse attitude towards V2G participating. This pattern is consistent with findings from conventional EV charging studies, where SOC plays a central role in charging decisions (Pan et al., 2019; Wang et al., 2021; Zhang et al., 2022). However, in a V2G context, higher SOC can also imply greater potential for discharging and earning financial benefits. This explains why the SOC attribute is insignificant for Class 1.

Similarly, the distance of the next planned trip has a positive effect on plug-in likelihood for Class 0 but no significant effect for Class 1, implying that longer upcoming trips increase the probability to plug in among more cautious users. This reflects more anticipatory planning behaviour and stronger range-related concerns in Class 0. In addition, the number of discharging cycles negatively affects plug-in decisions only for Class 0, pointing to concerns about potential battery degradation. This negative effect of discharging cycles has also been reported in the study of Huang et al. (2021). In contrast, Class 1, which are likely comprising more experienced EV users, shows no significant sensitivity to the distance of the next planned trip and discharging cycles. This suggests greater confidence in battery performance and V2G technology, as well as a reduced perception of battery-related risks. As a result, individuals in this class appear to place greater emphasis on other factors, such as cost savings, convenience, and location, when making plug-in decisions.

5.2.4. Access, convenience and location preferences

With respect to access, convenience, and location preferences, we examine the sensitivity of the two classes to walking time, waiting time, charging location, and parking duration.

Regarding time-related inconvenience, both walking time and waiting time negatively affect plug-in behaviour, consistent with findings in the existing literature towards conventional EV charging (Solvi Hoen et al., 2023; Yang et al., 2024). Clear heterogeneity emerges between the two classes. Class 1 exhibits a strong aversion to waiting time, whereas Class 0 appears largely insensitive to it. Besides, both classes dislike walking time, with Class 0 showing a stronger aversion than Class 1. This suggests that physical effort and access burden constitute the main practical barriers for Class 0, whereas Class 1 is more tolerant of such effort, likely due to greater familiarity with EV usage; however, Class 1 places greater emphasis on efficiency and operational reliability.

The parking time coefficient for both classes is positive and statistically significant, indicating that longer parking durations are valued in both groups, as they offer greater opportunities for V2G participation. Class 0 demonstrates a notably stronger sensitivity to parking time compared to Class 1, which again indicates higher requirements for them to plug in their EVs. In the V2G context, parking time has received limited attention in the literature, as it becomes particularly relevant when decisions are made at the level of daily routines. However, in the context of conventional EV charging, longer parking durations have also been found to positively influence charging behaviour (Wang et al., 2021).

In terms of location preferences, only Class 1 exhibits a clear disutility for shopping locations relative to home, likely due to the perceived inconvenience of finding parking near shopping areas. For this group, home and workplace locations are more strongly preferred. Similar patterns are reported by Kubli (2022), who finds that home charging is the most preferred option, followed by workplace charging and then public charging. In contrast, both working and shopping location coefficients are not statistically significant for Class 0. This suggests that cautious adopters do not strongly differentiate between charging locations once access-related inconvenience and battery-related risks are considered. One plausible explanation is that this segment contains a higher share of non-EV owners, who may have limited experience with how charging conditions differ across locations. Rather than responding to the location label itself, they may rely more on the explicit situational attributes provided in the scenarios to make the decision.

In summary, Class 0 reflects a "cautious adopter" segment of the population, more risk-averse and sensitive to cost savings, battery degradation, range anxiety, and access inconveniences. These respondents are more likely to be women or non-EV owners, consistent with groups identified in previous segmentation studies as being more hesitant toward new mobility technologies (Plötz et al., 2014; Axsen et al., 2016; Sovacool et al., 2018).

By contrast, Class 1 can be described as "confident EV pragmatists". Members of this class are more likely to be male or EV owners. They display moderate and relatively stable cost sensitivity across income groups, have minimal concerns about battery degradation, and are less influenced by minimum guaranteed battery level or current SOC level. These users place greater emphasis on efficiency and show lower sensitivity to inconvenience factors such as walking, indicating a pragmatic acceptance of minor inconveniences in exchange for the benefits of plugging in. Overall, Class 1 represents an experienced and pragmatic user group that is more open to trade-offs and faces fewer behavioural barriers to V2G participation.

5.3. Marginal Rate of Substitution (MRS) analysis

In this study, we compute and interpret the Marginal Rate of Substitution (MRS) for several key attributes in the LCL model to better understand the trade-offs between different attributes across the two latent classes. As shown in Equation (9), the MRS between attribute x_1 and x_2 is computed as the rate of partial derivatives of utility V with respect to each attribute.

$$MRS = \frac{\partial V/\partial x_1}{\partial V/\partial x_2} \tag{9}$$

All comparisons are made relative to the cost-saving coefficient, which serves as the monetary reference point for interpreting trade-offs. Specifically, we examine the MRS between walking time and cost saving, waiting time and cost saving, minimum guaranteed battery range and cost saving, discharging cycles and cost saving, and charging location and cost saving. Table 6 presents MRS values, providing quantitative insights into how respondents trade off monetary savings against behavioural and operational factors.

Across both classes and income groups, walking time is associated with substantially higher monetary compensation than waiting time. For example, compensating 10 min of walking requires between €5 and €9, whereas compensating 10 min of waiting requires approximately €3.2 to €3.5 for Class 1, and no compensation is required for Class 0. This difference suggests that physical access to charging infrastructure constitutes a more fundamental barrier than queueing delays. While waiting time may be partially mitigated through pricing or scheduling mechanisms, additional walking distance reflects spatial mismatches that are less amenable to monetary compensation alone.

Table 6
Results of the marginal rate substitution.

Marginal rate substitution	Class0	Class1
Walking time and cost savings for high income (euro per 10 mins)	−5.69	−5.30
Walking time and cost savings for middle income (euro per 10 mins)	−9.24	−6.26
Walking time and cost savings for low income (euro per 10 mins)	−6.15	−5.68
Waiting time and cost savings for high income (euro per 10 mins)	–	−3.23
Waiting time and cost savings for middle income (euro per 10 mins)	–	−3.81
Waiting time and cost savings for low income (euro per 10 mins)	–	−3.46
Shopping area and cost savings for high income (euro)	–	−3.16
Shopping area and cost savings for middle income (euro)	–	−3.73
Shopping area and cost savings for low income (euro)	–	−3.39
Discharging cycle and cost savings for high income (euro/cycle)	−0.77	–
Discharging cycle and cost savings for middle income (euro/cycle)	−1.25	–
Discharging cycle and cost savings for low income (euro/cycle)	−0.83	–
Minimum guaranteed battery range for high income (euro/km)	0.05	0.02
Minimum guaranteed battery range for middle income (euro/km)	0.09	0.02
Minimum guaranteed battery range for low income (euro/km)	0.06	0.02

We examine the MRS between charging location and cost savings to assess how users value convenient locations, such as home, relative to less preferred locations such as workplaces and shopping areas. Results indicate that public charging at shopping areas is least attractive for Class 1 respondents, requiring compensation of €3.16 for high-income, €3.73 for middle-income, and €3.39 for low-income users. The magnitude of the required compensation suggests that modest financial incentives may be insufficient to offset location-related inconvenience, highlighting the importance of aligning charging opportunities with routine and predictable activities.

With respect to the minimum guaranteed battery range, respondents are willing to accept approximately €0.02 to €0.09 in compensation for a 1 km reduction. These low MRS values suggest that limited adjustments to guaranteed range can be compensated financially, particularly when reductions are small and do not threaten users' perceived mobility security.

For the discharging cycles, Class 0 respondents require approximately €0.77 to €1.25 in compensation per additional cycle. This indicates that monetary compensation alone is unlikely to offset a large number of additional discharging cycles. As a result, limiting the frequency of V2G discharging events or complementing financial incentives with battery health protections and clear guarantees is likely to be important.

Across income groups, middle-income respondents consistently require higher compensation than either low- or high-income respondents. This pattern arises from the heterogeneous sensitivity to cost savings, with middle-income respondents having a lower sensitivity to cost savings than the other groups. As discussed in Section 5.2.2, this may come from different underlying motivations across income groups. Consequently, sensitivity to inconvenience does not scale linearly with income, suggesting that differentiated incentive designs may be more effective than uniform schemes.

6. Discussion and policy implications

The results presented in the previous section offer valuable insights that inform targeted policy recommendations. This section discusses the implications from three key perspectives: business model development, class-specific strategies, and infrastructure planning.

6.1. Business model development

The results provide clear guidance for the design of V2G business models, particularly regarding battery range guaranty and location-based incentives.

The study reveals EV owners' heterogenous preferences regarding the battery level at which they choose to begin charging, as well as their expectations for the minimum guaranteed battery range after participating in V2G. The result implies that a uniform value for the guaranteed battery range after discharge is not optimal. To improve user satisfaction and increase participation, V2G systems should offer personalised or dynamically adjustable thresholds tailored to individuals' driving needs. Allowing users to set their own minimum battery range can reduce range anxiety, enhance trust in the system, and encourage wider adoption.

Charging location plays an important role in shaping participation. The MRS results shows that public charging in shopping areas is associated with a clear disutility that requires non-trivial compensation, even for more confident users. This implies that financial incentives alone may be insufficient to make such locations competitive with home or workplace charging, especially if access inconvenience remains high. From a business model perspective, this suggests that V2G services should prioritise locations that align with predictable daily routines, such as home and workplace settings, where participation can be achieved with lower compensation levels.

When public charging is really important at specific locations, targeted and location-based incentives may be necessary to encourage participation. Rather than relying on offering fixed monthly or yearly benefits for V2G participation for all locations, flexible incentives schemes or dynamic pricing that reflect real-time system needs and local inconvenience levels are likely to be more effective (Latinopoulos et al., 2017). Overall, the results indicate that effective V2G business models should combine modest monetary incentives with user-controlled constraints and strategic location prioritisation.

6.2. Class-specific strategies

Building on the observed behavioural heterogeneity, this study identifies two distinct classes of respondents: cautious adopters (Class 0) and confident EV pragmatists (Class 1). These groups differ not only in their behavioural sensitivities but also in their sociodemographic characteristics. From a policy perspective, adopting a class-based approach that designs targeted strategies for each segment can lead to more effective outcomes than applying uniform measures across the entire population. Tailoring policies to specific behavioural and demographic profiles can support wider adoption of V2G technology and lead to a more efficient allocation of resources.

For cautious adopters (Class 0), who are more likely to be women and non-EV owners, participation is constrained by stronger behavioural barriers, including range anxiety, limited trust in V2G systems, and heightened sensitivity to access-related inconvenience. For this group, financial incentives play a more important role in triggering initial engagement. However, the MRS results indicate that monetary compensation alone may not fully offset perceived risks and inconvenience. As a result, incentive schemes targeting this group should be complemented by non-monetary measures, such as improving charger proximity, clear minimum battery guarantees, battery health assurances. From a policy perspective, targeted incentives for this group may be effective in lowering entry barriers, but they should be carefully designed to avoid perceptions of unfairness among more willing participants. Equity considerations are therefore central. Users in Class 1 already exhibit higher willingness to participate and may perceive disproportionate incentives for hesitant users as inequitable. A balanced strategy could combine targeted onboarding support for cautious adopters, such as higher initial rewards or risk-reducing guarantees with universal incentives that reward actual V2G participation regardless of user type. This dual approach supports behavioural change while maintaining fairness across user groups.

Battery degradation concerns is a non-negligible barrier for Class 0 users. Rather than addressing this concern through increasing payments, the results suggest that trust-building mechanisms are likely to be more effective. These include explicit battery warranty extensions, limits on discharging cycles, and regular feedback on battery health. Providing empirical evidence on battery degradation under V2G operation can further reduce perceived risk and encourage participation without imposing high recurring costs on operators.

Range anxiety affects both Class 0 and Class 1 and is closely linked to uncertainty in daily mobility needs. However, the MRS results indicate that the monetary valuation of minimum guaranteed battery range is relatively modest across all income groups, suggesting that range-related concerns can be partially offset through cost savings. This implies that offering moderate financial compensation alongside clearly defined minimum battery guarantees may be sufficient to alleviate range anxiety for many users.

For confident EV pragmatists (Class 1), participation decisions are jointly shaped by cost savings, convenience, and operational efficiency. This suggests that effective engagement of this group requires a combination of monetary incentives and measures that reduce both walking- and waiting-related frictions. Financial rewards can help compensate for moderate inconvenience, while improvements in access convenience and operational efficiency are equally important. Such measures include priority parking near building entrances, prioritised access to charging points, and reserved V2G-designated spaces. In addition, digital solutions, such as intuitive mobile applications, automatic preference settings based on habitual routines, and seamless authentication, can reduce effort and uncertainty, making plug-in behaviour easier to integrate into daily activities.

6.3. *Infrastructure planning*

Both user classes exhibit strong aversion to walking time, while Class 1 users additionally show sensitivity to waiting time. These findings suggest that infrastructure planning, such as the optimal design of the location and the capacity of the charging station, which support short walking and waiting time can be very cost-effective. Practical measures include reserving spaces close to building entrances for V2G-enabled vehicles, prioritised access to charging points, and reserved V2G-designated spaces. In addition, adequate charger capacity or queueing jumping system is essential to limit queuing.

Location-specific effects further inform infrastructure priorities. The strong disutility associated with public charging in shopping areas for Class 1 users indicates that such locations are less suitable for sustained V2G participation, even when financial compensation is provided. When considered alongside the significant influence of parking duration, these results suggest that infrastructure investment should prioritise locations with predictable and sufficiently long parking times that aligns with people’s daily routines, such as residential areas, workplaces, and dedicated mobility hubs. In contrast, leisure-oriented locations with shorter and more uncertain parking durations are likely to contribute less effectively to reliable V2G supply unless accompanied by substantial improvements in accessibility and capacity.

7. Conclusion and future work

7.1. *Conclusion*

This paper examines people’s willingness to plug in their V2G-enabled EVs at each parking opportunity within their daily routines, advancing the V2G literature that has largely focused on EV purchase or rental decisions and contractual participation. We adopt a flexible, routine-aligned perspective in which plug-in behaviour reflects both recharging needs and the willingness to participate in V2G. Using a stated choice experiment conducted in the Netherlands, we analyse how situational, behavioural, and socio-demographic factors jointly shape plug-in decisions among both current EV owners and potential future users, thereby providing new behavioural evidence on V2G participation and its equity implications.

The latent class analysis identifies two distinct user segments: cautious adopters and confident EV pragmatists. Cautious adopters, more often women and non-EV owners, exhibit higher risk aversion and perceived uncertainty. Their main participation barriers come from strong range anxiety, concerns about battery degradation, and pronounced sensitivity to access-related inconvenience, particularly walking time. As a result, their plug-in decisions are primarily driven by a combination of recharging needs and financial compensation from V2G participation. In contrast, confident EV pragmatists, more frequently men and EV owners, display greater confidence and a higher overall willingness to participate in V2G activities. Likely due to their prior EV experience and pragmatic mindset, they exhibit limited range anxiety and fewer battery-related concerns. Instead, their decisions place greater emphasis on cost savings, convenience, and operational efficiency, including walking and waiting time. This group also shows clear preferences for home and workplace charging over public charging in shopping areas, highlighting the importance of aligning V2G participation with stable and repeatedly visited locations in daily routines.

These findings underscore the need for segment-specific strategies to support V2G adoption. For cautious adopters, targeted financial incentives to encourage initial participation, combined with minimum battery range guaranty and battery health assurances, can help reduce perceived risks, build trust, and foster early engagement. For confident EV pragmatists, combining monetary incentives with improvements in accessibility and operational efficiency, such as better charger placement and reduced access delays, is likely to be more effective.

Overall, the results suggest that flexible, routine-aligned schemes are more effective than rigid behavioural requirements. From an infrastructure planning perspective, the results further indicate that increasing monetary rewards alone is unlikely to overcome participation barriers if access inconvenience remains high. Improving charger proximity and reducing walking distance and waiting time are more effective than increasing V2G payments, particularly for more cautious users. Financial incentives should therefore be viewed as a complement to investment in infrastructure design and service quality, rather than a substitute. Moreover, the strong disutility associated with public charging in shopping areas suggests that such locations are unlikely to support sustained V2G participation through financial compensation alone. Priority should therefore be given to deploying charging infrastructure near homes and workplaces in the early stages of V2G rollout. Where plug-in participation is required at specific locations, targeted, location-based dynamic pricing schemes may offer a more effective solution.

7.2. Future work

This study has several limitations, which also point to directions for future research on willingness to participate in V2G. First, attitudinal, psychological, and social factors, such as social recognition, peer influence, and familiarity with V2G, were not included due to survey duration constraints. Incorporating these factors in future studies could provide a more comprehensive understanding of behavioural motivations. Second, the results provide only a static snapshot of behaviour and therefore do not capture how preferences evolve over time as users gain experience with V2G. Future research could address this limitation by applying longitudinal or dynamic modelling approaches. In addition, although the present analysis focuses on individual plug-in behaviour, future work could explicitly examine how institutional arrangements and employer-provided incentives interact with individual preferences, particularly in workplace settings. Finally, further research could extend the analysis to mode choice behaviour, including the role of privately owned V2G-equipped EVs and V2G-enabled shared mobility services such as carsharing.

CRediT authorship contribution statement

Qiaochu Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Kuldeep Kavta:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Shadi Sharif Azadeh:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Gonçalo H.A. Correia:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

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.

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Appendix A. Survey introduction to V2G technology

What is Vehicle-to-Grid (V2G)?

V2G technology allows an electric vehicle (EV) do more than just drive. This EV can charge its battery from the power grid, but it can also send power back when it's needed. Think of this car like a "battery on wheels," storing energy when there's lots of it (like on sunny or windy days) and sharing it back when everyone needs more power.

A smart system manages all of this for the car owner. It picks the best times to charge the EV with cheap electricity and the best times to sell electricity back to the grid, so car owners save money and help keep the lights on for everyone. However, the car has to be plugged into special chargers.

Fig. A1. Illustration of V2G integration. Adapted from Signature Electric (2018), "Vehicle-to-Grid: Delivering the Future of Energy."

Opportunities and Challenges of the Technology.

Save Money: Your car charges up when electricity is cheap and sells it back when prices are high.

Balance the Grid: V2G helps balance energy by storing extra renewable power and supplying it to the grid when it's needed.

Impact on the Environment: V2G makes it easier to use clean, renewable energy like solar and wind, cutting down on fossil fuels and lowering carbon emissions.

Battery Life: Charging and discharging may gradually affect your car's battery over time, similar to what happens with a phone battery.

Automatic Control: The system decides when to charge and discharge your car, so you won't control it yourself.

Data Privacy: V2G systems might collect information about how you use energy and charge your car. It's important that this data is kept safe and follows privacy rules.

Assume that you own an EV and have a valid driving license. Imagine a typical weekday when you use your EV equipped with this V2G technology. When you drive to places like work or shopping areas or return home for the night, you might have a chance to plug in your vehicle at a V2G charging station.

Terms that are important to consider in what comes next:

- Walking time to the V2G station: Sometimes, the parking spot where you can use V2G is not at home; it's in a parking lot somewhere in your neighborhood.
- Waiting time at the V2G station: Sometimes these parking spots are full, and you need to wait for a spot to become available.
- Battery range at the end of the stay: Whatever your charger decides to do, putting power on the battery or transferring power from the battery to the grid, the system guarantees that at the end of the parking time, you have that battery level.
- Estimated daily electricity cost savings: By plugging in your vehicle for that duration of parking, you have an expected daily saving compared to not using V2G.
- Expected (partial) discharging cycles: The estimated number of times your EV's battery will discharge back to the grid during its parking period. These don't need to be full charging and discharging cycles; the system may only discharge a portion of the battery each time.

Appendix B. BL model specification and results

The BL model assumes homogeneous preferences across individuals and expresses the utility of each alternative as a function of observed attributes and socio-demographic characteristics. To account for systematic behavioural variation, we include interaction terms between key attributes and socio-demographic factors. The systematic utility of choosing to plug in (alternative 1) for respondent r is specified in Equation (7). The utility of not plugging in (alternative 0) is the reference alternative.

$$V_{r1}^{BL} = \beta_0 + \beta_{LW} \cdot LW + \beta_{LS} \cdot LS + \beta_{PT} \cdot PT + \beta_{DT} \cdot DT + \beta_{CS} \cdot CS + \beta_{WKT} \cdot WKT + \beta_{WTT} \cdot WTT + \beta_C \cdot C + \beta_{IL} \cdot IL + \beta_{IH} \cdot IH + \beta_{SOC\times EV} \cdot SOC \cdot EV + \beta_{SOC\times NOEV} \cdot SOC \cdot (1 - EV) + \beta_{BG\times NOEV} \cdot BG \cdot (1 - EV) \tag{7}$$

The estimation results of the BL models are presented in Table B1. For comparison, we display the results of a baseline model that includes only the coefficients that pertain to the attributes of the alternatives, excluding interaction terms and socio-demographic variables.

Table B1
Estimation results of BL models.

Attributes in choice tasks	Simple BL			BL with interactions and socio-demographic variables		
	Value	**Std err**	**p-value**	**Value**	**Std err**	**p-value**
Alternative specific constant (ASC)	0.807	0.22	0.00	0.846	0.20	0.00
Cost saving (*CS*)	0.128	0.01	0.00	0.129	0.01	0.00
Discharging cycles (*C*)	−0.047	0.02	0.02	−0.052	0.02	0.01
Distance of next trip (*DT*)	0.005	0.00	0.00	0.005	0.00	0.00
Location: shopping area (*LS*)	−0.313	0.12	0.01	−0.349	0.12	0.00
Location: workplace (*LW*)	−0.204	0.11	0.06	−0.215	0.11	0.05
Parking time (*PT*)	0.074	0.02	0.00	0.073	0.02	0.00
Waiting time (*WTT*)	−0.047	0.01	0.00	−0.047	0.01	0.00
Walking time (*WKT*)	−0.082	0.01	0.00	−0.083	0.01	0.00
SOC (*SOC*)	−0.008	0.00	0.00	–	–	–
Minimum battery guarantee (*BG*)	0.004	0.00	0.00	–	–	–
Monthly household income $>$ 6000 euros (*IH*)	–	–	–	0.266	0.10	0.01
Monthly household income $\leq$ 3000 euros (*IL*)	–	–	–	0.183	0.09	0.04
SOC for EV owners ($SOC \times (EV = 1)$)	–	–	–	−0.005	0.00	0.00
SOC for non-EV owners ($SOC \times (EV = 0)$)	–	–	–	−0.009	0.00	0.00
Minimum guaranteed battery range for non-EV owners ($BG \times (EV = 0)$)	–	–	–	0.005	0.00	0.00
Estimation indicators						
Nbr of parameters	11			14		
Sample size	3606			3606		
Null log likelihood	−2499.49			−2499.49		
Final log likelihood	−2212.71			−2195.39		
Likelihood ratio test (null)	573.549			608.189		
Rho square (null)	0.115			0.122		
Akaike Information Criterion	4447.428			4418.788		
Bayesian Information Criterion	4515.522			4505.453		

Comparing the baseline model with the extended model that includes interactions and socio-demographic variables, we find that the latter offers a better model fit. Specifically, the extended model has lower AIC and BIC values, indicating a more favourable trade-off between model complexity and goodness-of-fit. Additionally, it achieves a higher log-likelihood and a greater McFadden's Rho-squared value, suggesting an improvement in model fit. The likelihood ratio statistic increases from 573.55 to 608.19, confirming that the inclusion of additional variables significantly enhances model performance. Importantly, the core attribute coefficients remain stable in value and significance, demonstrating that the main behavioural effects are consistent across the two model specification. The added socio-demographic and interaction terms are significant and behaviorally plausible, showing that the richer model enhances explanatory power while preserving consistency in the core results.

We now examine the estimated parameters to gain deeper insights into people’s preference in plug-in behaviour. The ASC captures the average preference for plugging in EVs versus not plugging in that is not explained by the explanatory variables. Results indicate that this parameter is significant, suggesting an underlying preference among respondents for choosing the plug-in option that was not possible to explain through the collected variables. Additionally, the estimated coefficients for cost savings are both positive and highly significant, highlighting a strong sensitivity to monetary benefits.

When comparing different locations, both shopping areas and workplace areas are associated with a reduction in utility relative to home charging, with especially strong disutility for shopping locations. This likely reflects concerns over convenience, limited parking availability or shorter duration of stay. Even if this is being captured by the parking time duration, the activity of going to shopping may have a special disutility for its systematic short duration in comparison to other activities. The milder disutility observed at workplaces may be attributed to restricted access to charging infrastructure or current lack of employer support.

Regarding time-related variables, we observe that parking time is as expected positively and significantly associated with the utility of plugging in. This indicates that people are more willing to plug-in when they plan to leave their EVs parked for longer periods, suggesting a preference to monetise idle time. In contrast, both walking time and waiting time have negative and significant co-efficients, indicating that these forms of inconvenience reduce the attractiveness of plug-in options.

Regarding the SOC, the estimated coefficient is negative and highly significant. This suggests that a higher battery SOC reduces the utility of plugging in, aligning with findings from previous studies on EV charging preferences. The logic is that when the battery is already at a high level of charging, users feel less compelled to plug in, even with potential benefits of V2G. Evidently this would be the case in the absence of contractual obligations of minimum plug-in duration.

The number of discharging cycles also carries a negative and significant coefficient. As the expected number of cycles increases, utility of plugging in decreases, indicating that respondents are indeed concerned about battery degradation. They seem to associate a higher number of cycles with more wear and tear, making the plug-in option less appealing.

Looking at heterogeneity in SOC sensitivity with regards to owning or not an EV, we find that non-EV owners are more sensitive (−0.009) than EV owners (−0.005), with both coefficients being highly significant ($p < 0.001$). This suggests that non-EV owners may experience greater range anxiety or unfamiliarity with EV battery usage, leading to stronger aversion to lower SOC.

We further explored the minimum guaranteed battery range. The results show that only non-EV owners exhibit a significant and positive response to the minimum battery guarantee. This indicates that providing assurance about minimum battery range boosts their utility, reflecting concerns over range anxiety. In contrast, EV owners do not appear to value this guarantee as much, possibly because they trust the system or are more familiar with managing battery levels in everyday use.

Lastly, we observe that both low- and high-income groups exhibit higher overall utility for plugging in compared to the middle-income group. However, the underlying motivations likely differ. High-income respondents may be more influenced by factors such as such as interest in technology or sustainability when evaluating V2G participation, while low-income respondents are likely more cost-sensitive and therefore more responsive to economic incentives associated with V2G participation. The middle class may just be more indifferent to this technology when compared to these two groups. We can definitely say that there is no linear effect of income on the likelihood of plugging in.

Appendix C. LCL model specification and results (including non-traders)

We conducted additional estimations, including non-traders, and explored latent class specifications with a higher number of classes to assess whether non-trading behaviour could be captured as a distinct segment. However, none of the tested specifications simultaneously identified a separate non-trader class and achieved a satisfactory BIC. As the number of classes increased, the model became substantially more parameter-intensive, and model performance deteriorated in terms of BIC.

In this section, we therefore report the three-class latent class model estimated on the full sample, including non-traders, in Table C1. This specification yields the lowest BIC among the full-sample models while maintaining a clear, behaviourally interpretable segmentation. Non-traders are not isolated into a separate class; instead, they are probabilistically allocated across the three behavioural classes alongside traders.

Table C1
Estimation results of LCL models with non-traders.

	Class 0: confident EV pragmatists			**Class 1: degradation-sensitive group**			**Class 2: range sensitive group**		
Attributes in choice tasks	**Value**	**Std err**	**p-value**	**Value**	**Std err**	**p-value**	**Value**	**Std err**	**p-value**
Alternative specific constant (*ASC*)	1.216	0.441	0.01	−0.310	1.084	0.78	0.801	0.853	0.35
Minimum battery guarantee (*BG*)	0.003	0.002	0.06	0.003	0.004	0.49	0.014	0.003	0.00
Cost saving × high income (*CS* × *IH*)	0.153	0.037	0.00	0.189	0.048	0.00	0.213	0.105	0.04
Cost saving × middle income (*CS* × *IM*)	0.087	0.024	0.00	0.242	0.044	0.00	0.128	0.054	0.02
Cost saving × low income (*CS* × *IL*)	0.106	0.032	0.00	0.065	0.343	0.85	0.237	0.093	0.01
Discharging cycles (*C*)	0.026	0.043	0.54	−0.264	0.086	0.00	−0.134	0.062	0.03
Distance of next trip (*DT*)	−0.004	0.003	0.20	0.0003	0.005	0.95	0.029	0.009	0.00
Location: shopping area (*LS*)	−0.395	0.257	0.12	−0.444	0.580	0.44	0.352	0.603	0.56
Location: workplace (*LW*)	−0.101	0.287	0.73	−0.373	0.696	0.59	−0.240	0.546	0.66
Parking time (*PT*)	0.076	0.029	0.01	−0.001	0.053	0.98	0.234	0.082	0.00
SOC (*SOC*)	−0.002	0.002	0.15	0.002	0.003	0.50	−0.032	0.006	0.00
Waiting time (*WTT*)	−0.016	0.017	0.34	−0.153	0.049	0.00	−0.040	0.031	0.19
Walking time (*WKT*)	−0.076	0.021	0.00	−0.136	0.055	0.01	−0.151	0.041	0.00
Class membership function									
Class intercept	–	–	–	−1.233	0.466	0.01	−0.658	0.255	0.01
EV ownership (1: with EVs; 0: without EVs)	–	–	–	0.718	0.314	0.02	−0.758	0.342	0.03
Gender (1: women; 0: men)	–	–	–	0.042	0.278	0.88	0.717	0.265	0.01
Estimation indicators	**Value**								
Nbr of parameters	45								
Sample size	740								
Observations	4440								
Null log likelihood	−3077.573								
Final log likelihood	−2506.688								
Likelihood ratio test (null)	1141.772								
Rho square (null)	0.185								
Rho bar square (null)	0.171								
Akaike Information Criterion	5103.375								
Bayesian Information Criterion	5310.675								

The LCL model with non-traders refines, rather than overturns, the behavioural segmentation obtained from the LCL model without non-traders. Specifically, it separates the original “cautious adopters” segment into two more distinct groups: a degradation-sensitive segment (Class 1 in Table C1) and a range-sensitive segment (Class 2 in Table C1). No qualitatively new behavioural regime emerges, and the overall segmentation logic is therefore preserved.

Across the two estimations, the key taste parameters remain qualitatively stable: coefficients that are statistically significant retain the same signs as in the LCL model without non-traders. The main difference concerns the location effects: the coefficient for the shopping location is no longer statistically significant in the LCL model including non-traders. A plausible explanation is that, once the model allows for additional preference heterogeneity and retains non-traders, location-related variation is absorbed by the latent segmentation and by other attributes (e.g., convenience and battery-related variables). The core behavioural patterns remain unchanged: for example, cost-saving has a positive effect on plug-in utility; degradation concerns and SOC sensitivity are segment-specific; and convenience attributes have a negative effect on plug-in utility. Therefore, including non-traders does not affect the core conclusions of our paper.

The main differences arise in the class membership function. Relative to Class 0, EV ownership now significantly increases the probability of belonging to the degradation-sensitive segment (Class 1), while gender does not significantly distinguish Class 1 from Class 0. By contrast, non-EV owners and women are more likely to belong to the range-sensitive segment (Class 2), consistent with the patterns observed in the LCL model without non-traders. Overall, these results indicate that including non-traders primarily refines how socio-demographics map onto behavioural segments, without altering the core preference trade-offs. Taken together, the robustness analysis confirms that the main behavioural conclusions are not driven by the exclusion of non-traders.

To better visualise how class membership probabilities vary across gender and EV ownership, we calculate the probabilities using Equation (5) and present the results in Fig. C1.

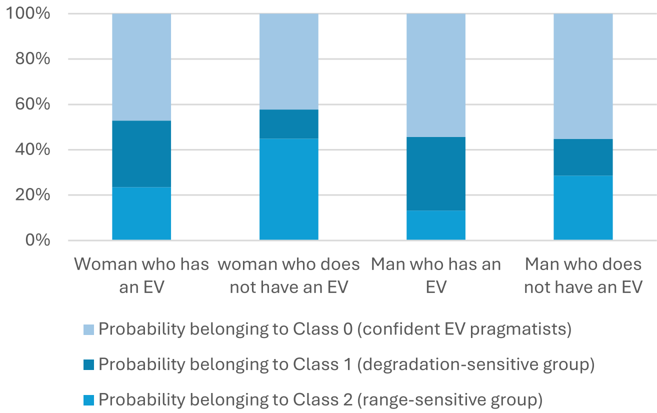

Fig. C1. Class membership probabilities across gender and EV ownership profiles

The marginal rate of substitution (MRS) values after including non-traders are reported in Table C1. Comparing Table C1 with Table 6 shows that the inclusion of non-traders influences the MRS estimates. Although several MRS values remain within a comparable range, such as those for discharging cycles and minimum guaranteed battery range, other MRS values change more noticeably once non-traders are included, such as those for waiting time. This suggests that non-traders can affect the magnitude of the estimated behavioural valuations; however, the extent of this influence varies across attributes.

Table C1
Results of the marginal rate substitution (with non-traders).

Marginal rate substitution	Class 0: confident EV pragmatist	Class 1: degradation-sensitive group	Class 2: range sensitive group
Walking time and cost savings for high income (euro per 10 mins)	−4.97	−7.20	−7.09
Walking time and cost savings for middle income (euro per 10 mins)	−8.74	−5.62	−11.80
Walking time and cost savings for low income (euro per 10 mins)	−7.17	–	−6.37
Waiting time and cost savings for high income (euro per 10 mins)	–	−8.10	–
Waiting time and cost savings for middle income (euro per 10 mins)	–	−6.32	–
Waiting time and cost savings for low income (euro per 10 mins)	–	–	–
Discharging cycle and cost savings for high income (euro/cycle)	–	−1.40	−0.63
Discharging cycle and cost savings for middle income (euro/cycle)	–	−1.09	−1.05
Discharging cycle and cost savings for low income (euro/cycle)	–	–	−0.57
Minimum guaranteed battery range for high income (euro/km)	0.02	–	0.07
Minimum guaranteed battery range for middle income (euro/km)	0.03	–	0.11
Minimum guaranteed battery range for low income (euro/km)	0.03	–	0.06

Data availability

The authors do not have permission to share data.

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