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Understanding user preferences regarding vehicle-to-grid (V2G): A latent class choice analysis

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ABSTRACT

The vehicle-to-grid (V2G) innovation—which enables electric vehicles to return stored electricity to the grid—holds significant potential to facilitate the integration of intermittent renewable energy and support climate goals. However, user preferences and how they vary across different user groups remain poorly understood, even though V2G's success depends on driver participation. This study addresses this gap by conducting a stated choice experiment with 1,018 participants in the Netherlands. Participants chose between hypothetical V2G contracts based on four key attributes: financial compensation, guaranteed driving range, minimum plug-in time, and battery degradation—each varied at three levels. Using a latent class choice model, the analysis identified four distinct user preference profiles (or classes). Overall, guaranteed range and plug-in time were found to outweigh financial incentives for most users. The largest class (43% of users) prioritizes guaranteed range and shows the lowest sensitivity to financial incentives. The second-largest class (29%) also prioritizes guaranteed range, while assigning the least importance to plug-in time. The third class (18%) places the greatest importance on reducing plug-in time, followed by increasing guaranteed range. The smallest class (10%) is primarily motivated by financial compensation. The study further examines how user characteristics—such as socio-demographic, household, car use, and attitude factors—relate to class membership. The analysis provides a comprehensive overview of how these characteristics influence user preferences. These findings offer valuable insights into the diversity of V2G user preferences and inform targeted policy recommendations.

1. Introduction

To mitigate climate change, numerous governing bodies have set ambitious decarbonization targets (UNCCC, 2015; European Commission, 2021; U.S. Department of Energy, 2023). Key aspects of such targets aiming to reduce greenhouse gas emissions involve increasing the use of renewable energy across various sectors and electrifying energy-intensive sectors, such as transportation (EEA, 2017; IEA, 2021; Klimaatakkoord, 2022; Rijksoverheid, 2022; Sims et al., 2014; Markard and Rosenbloom, 2022; Geels et al., 2017b). However, the rapidly growing share of intermittent renewables and the widespread adoption of electric vehicles (EVs) pose challenges

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to the electricity grid, affecting grid stability and security of supply (IEA, 2020; IRENA, 2020; Alshahrani et al., 2019; Das et al., 2020; Habib et al., 2018; Li and Lenzen, 2020).

The vehicle-to-grid (V2G) innovation holds significant promise as a source of flexibility to regulate the increasing loads on the electricity grid by efficiently coupling the transport and electricity sectors (Heffron et al., 2020; Robinius et al., 2017a; Fridgen et al., 2020; Brown et al., 2018; Lund, 2009; Xu et al., 2023). Fundamentally, it describes a system in which EV batteries serve as mobile storage, providing demand response services to the grid to manage load variations. This can occur either unidirectionally (referred to as smart charging), which regulates charge rates to meet system needs, or bi-directionally, where stored electricity can be returned to the grid when needed (Robledo et al., 2018; Mwasilu et al., 2014; Kempton and Tomić, 2005a, 2005b; Lund and Kempton, 2008; Niesten and Alkemade, 2016; Noel et al., 2017; Sovacool et al., 2017a). By integrating renewable energy with two key flexibility sources—namely, storage and dispatchable power—V2G not only has the potential to encourage EV adoption but can also help mitigate the challenges of renewable energy intermittency. Consequently, V2G can reduce the need for extensive investments in grid expansion, international transmission, or static storage, particularly as renewable energy and EV penetration continue to rise (Brown et al., 2018; Geels et al., 2017a; Hannan et al., 2022).

The potential of V2G has garnered widespread attention from academia, industry, and policy-makers, leading to a steady increase in studies and trials globally, particularly in the Netherlands, Germany, the UK, and the US. However, a review of academic V2G literature reveals a predominant focus on technical aspects (Robinius et al., 2017b; Flath, 2013; Mwasilu et al., 2014; Verzijlbergh, 2013; Brown et al., 2018; Thellufsen and Lund, 2017), with limited consideration given to social aspects, as noted in some recent studies (Sovacool et al., 2017b; 2018b; Bibak and Tekiner-Moğulkoç, 2021; Gschwendtner et al. 2021; Park Lee, 2019). Most trials also concentrate on technical and regulatory aspects of V2G implementation (V2Ghub, 2024; EV Consult, 2018), often overlooking the social context. This is problematic because V2G—as a demand-side innovation—relies heavily on user behavior, which plays a crucial role in its adoption and effectiveness; without active user participation, V2G cannot fully realize its potential.

The literature indicates four main user-related barriers to V2G adoption: loss of flexibility to use the car at any time, for instance, due to extended plug-in periods; battery degradation concerns, which can lead to vehicle depreciation and heightened EV range anxiety; data privacy issues arising from distrust in data sharing between EVs and third-party service providers; and uncertainty about return on investment due to the high initial costs of EVs and bi-directional chargers, as well as revenue uncertainty caused by factors like market saturation (Bakhuis et al., 2025a; Shareef et al., 2016; Sovacool et al., 2017b; Chen et al., 2020; Franke et al. 2012, Hidrue et al., 2011, Parsons et al., 2014, Noel et al., 2019b). These barriers might be mitigated by offering sufficient financial incentives, guaranteeing minimum driving ranges, and providing an immediate charge button that allows users to stop grid service and charge at full capacity (Gschwendtner et al., 2021; Sovacool et al., 2017b; Noel et al., 2019b).

While a growing number of studies have explored V2G implementation from a sociotechnical perspective, for instance, qualitatively identifying key user-related barriers and acceptance factors (Kester et al., 2018; Noel et al., 2019a; Sovacool et al., 2017b, 2018, 2019; van Heuveln et al., 2021; Meelen et al., 2021; Lucas-Healey et al., 2022; Lucas-Healey et al., 2024), and a few have focused on quantitatively uncovering specific user preferences for adoption (Geske and Schumann, 2018; Kubli et al., 2018; Noel et al., 2019b; Parsons et al., 2014; Chen and Lai, 2024), there remains a need for a deeper exploration of these factors. Specifically, understanding the significance of the remaining V2G user-related barriers, determining the types and levels of incentives required to overcome them, and assessing how these factors vary across different user groups based on their characteristics remain crucial areas of investigation.

To bridge this gap and enhance the understanding of user preferences relating to V2G, we conducted a stated choice experiment in the Netherlands. The objective of this study is twofold; first, to gain a more nuanced understanding of preferences of potential V2G users, and second, to explore how these preferences vary based on user characteristics. As such, the central research question addressed in this paper is: *"What are the preferences of potential users towards vehicle-to-grid (V2G) contract elements, and how are these preferences shaped by user-related factors?"*.

In the stated choice experiment, participants answered twelve choice-questions, selecting between two hypothetical V2G contracts. They also completed around forty-five supplementary questions to provide details about their personal characteristics. Eligibility criteria included residence in the Netherlands, a valid driver's license, and regular access to a car (whether owned, leased, rented, or shared). A representative sample of 1,018 respondents completed the survey, with quota's ensuring diversity in age, gender, education, and car type (electric or fossil fuel). To analyze respondents' preferences, a latent class choice model (LCCM) was estimated, revealing four distinct groups with varying sensitivities to the contract attributes.

The subsequent sections of this paper are organized as follows. Section 2 presents the literature review. Section 3 outlines the experiment design and data collection process. Section 4 explains the methodology. Section 5 presents the results. Section 6 discusses the practical implications, and finally, Section 7 offers conclusions drawn from our findings.

2. Literature review

Numerous studies have examined V2G primarily from a technical perspective, generally finding few technical barriers aside from needed efficiency improvements (Robinius et al., 2017b; Flath, 2013; Mwasilu et al., 2014; Verzijlbergh, 2013; Kempton and Tomić, 2005a). System optimization research further highlights V2G's potential to enhance electricity system flexibility (Brown et al., 2018; Thellufsen and Lund, 2017; Xu et al., 2023). However, user-related factors consistently emerge as key obstacles to widespread adoption (Sovacool and Hirsh, 2009; Sovacool et al., 2017b; 2018b; Gschwendtner et al., 2021; Bakhuis et al., 2025a; Noel et al., 2019a; Kester et al., 2018). This section reviews previous choice experiments—organized by study context—to assess current knowledge of user preferences, behavior, and acceptance of V2G. These insights inform the selection of V2G contract attributes and levels for our own choice experiment (Section 3.2).

In the United States (US), Parsons et al. (2014) investigated consumer demand for V2G-enabled EVs, laying foundational groundwork in the field. Survey respondents compared their preferred gasoline vehicle with two V2G-enabled EVs, evaluating trade-offs among EV attributes and V2G contract elements such as plug-in time and guaranteed minimum range. Using a latent class model, the authors found that consumers perceived significant inconvenience from reduced flexibility and heavily discounted uncertain V2G payments—requiring compensation between $2,368–$8,622, well above estimated market values (∼$2,900). They suggest that V2G would require more flexible participation models, such as pay-as-you-go schemes or upfront cash payments, to gain traction. In a follow-up study, Hidrue and Parsons (2015) found that US consumers' willingness-to-pay for V2G-enabled EVs remained below projected costs under all battery price projections. Key deterrents included range anxiety, restrictive V2G contract terms, and high battery costs.

In the European context, Geske and Schumann (2018), using a latent class choice model with German consumers, found that range anxiety and minimum driving range were the most influential factors shaping willingness to participate in V2G. They argued that even without remuneration, addressing these concerns could yield high participation rates. In contrast, Kajanova et al. (2022) found that remuneration was critical in Slovakia, with higher payments increasing willingness to sell energy to aggregators.[1] Gschwendtner and Krauss (2022) explored the appeal of V2G-enabled car-sharing in Germany and Switzerland, finding it more attractive than regular EV car-sharing in 56.1% of cases and conventional car-sharing in 74.2%. Building on this, Suel et al. (2024) demonstrated that car-sharing users in Switzerland were willing to shift booking times for financial incentives—averaging 22.4 CHF and 35.5 CHF per hour ($23.5–$37.2) depending on the trip purpose, timing, and user characteristics. This flexibility is key for aligning plug-in behavior and V2G charging with grid needs.

Across the five Nordic countries, Noel et al. (2019b) employed a setup similar to Parsons et al. (2014), asking respondents to choose between their preferred gasoline vehicle and various EVs, some with V2G capability. Using a mixed logit model, they found that V2G capability—when not tied to burdensome contracts—had a significantly positive effect in two countries, with willingness-to-pay estimates between €4,000 and €5,200, but offered no added value in the other three. The authors suggest that increased education and awareness could enhance V2G's role in EV adoption where its benefits remain unrecognized. Using the same dataset, Chen et al. (2020) applied hierarchical regression analysis and found that V2G capability and charging time were the strongest predictors of EV adoption. Notably, former EV owners valued V2G more highly than current EV or gasoline vehicle owners, implying that V2G may serve a marginal incentive or 'tipping point' for EV adoption.

In the Netherlands, Zonneveld (2019) studied how EV users respond to compensatory V2G contracts, using a web-based survey and a multinomial logit model. The three most influential contract elements were remuneration, guaranteed driving range, and the number of discharging cycles (impacting battery degradation). Building on this, Huang et al. (2021) explored Dutch EV drivers' preferences for V2G contracts with an aggregator, particularly under varying charging speeds. They found that required plug-in time, financial compensation, the number of discharge cycles, and guaranteed battery levels were key factors. Crucially, the relative importance of these elements shifted with charging speed: as recharging became faster, the perceived value of a guaranteed minimum battery level was halved, and the need for compensation also declined.

Beyond the US and Europe, V2G choice studies remain limited. In South Korea, Lee et al. (2020) estimated a dichotomous choice model, finding an average willingness to accept of KRW 9821 ($8.83) per month. Key concerns included grid-connection inconvenience and battery degradation. In Australia, Gong et al. (2021) used a best-worst scaling model to examine attitude towards V2G at workplaces, finding that commuters valued cost savings over sustainability, while employers cited high costs and uncertain returns as key barriers. Furthermore, Philip et al. (2023) estimated a mixed logit model, finding that including V2G capabilities in EV purchase decisions increased consumer appeal, with willingness to pay ranging from AUD 2,319 to AUD 5,346 ($1,520 to $3,510) depending on the type of V2G functionality offered (i.e., vehicle-to-grid, vehicle-to-home, or both).

Comparing the findings across contexts reveals several notable differences. While Geske and Schumann (2018) found limited importance for remuneration in Germany, studies from the Netherlands and Slovakia highlight financial compensation as a key driver of V2G participation. Such discrepancies may reflect differences in experimental design, modelling approaches, or sample characteristics. Broader contextual factors—such as socio-demographics, national legislation, EV incentives, and mobility cultures—also shape user preferences (Sovacool et al., 2017b). For instance, Western Europe's stronger public transport infrastructure and higher EV adoption contrast with car-centric norms in the US and Australia, where EV uptake remains comparatively low (IEA, 2023). Meanwhile, emerging car-sharing ecosystems in countries like Germany and Switzerland may provide new pathways for V2G integration.

Building on insights from the V2G literature, the current study addresses two key knowledge gaps. First, prior research has typically examined a narrow set of user characteristics—such as age, gender, and income—often relying on small or homogenous samples. In contrast, we analyze a broader range of socio-demographic, household, car use, and attitudinal factors, using a large and diverse sample that includes both EV and non-EV drivers. Second, few studies have examined preference heterogeneity in depth. We address this by applying a latent class choice model—an approach previously used in only two V2G studies, both based on older data (2009 and 2013) and samples dominated by fossil-fuel vehicle drivers (Parsons et al., 2014; Geske and Schumann, 2018). Using recent data (2023), which reflect a rapidly evolving context of rising EV adoption and increasing grid congestion, we identify distinct user segments with differing priorities. This helps reconcile earlier mixed findings, particularly regarding financial incentives, which are found not to be universally decisive.[2] Beyond these core contributions, our sample of 1,018 exceeds prior Dutch studies in size and diversity

[1] In the context of V2G, an aggregator is a third-party entity that coordinates and manages the combined energy stored in EVs, optimizing their charging and discharging to provide electricity grid services or participate in energy markets.

[2] A multinomial logit model, even when applied on the same dataset, would not have revealed these nuanced patterns.

(Zonneveld, 2019: N = 96; Huang et al., 2021: N = 148), strengthening its statistical robustness and policy relevance.

3. Experiment design and data collection

This study aims to uncover potential users' preferences towards V2G contract elements and how these preferences are influenced by user-related factors. To achieve this, we conducted a stated choice experiment, administered through an online stated preference survey on the Qualtrics platform.

This research forms part of a broader effort to analyze the V2G dataset. While the current study focuses on contract attribute valuation using the choice data (stated preferences), a complementary study examines participants' stated intentions regarding participation, along with the underlying drivers and barriers (Bakhuis et al., 2025b).

3.1. Stated choice experiment design

In the stated choice experiment, we presented hypothetical V2G contracts that participants could choose from, enabling us to analyze their preferences for various V2G contract elements. The experiment featured twelve choice sets, each comparing two hypothetical contracts.

Our primary goal was to design an experiment that was both realistic and accessible, as well as to obtain valuable insights while remaining clear for our target audience: adult Dutch residents with a driver's license and regular access to a car. To this end, we included only essential elements in the V2G contracts and ensured that the levels were easy to interpret. Each V2G contract was characterized by four key contract elements (or attributes), each varied across three equidistant levels (refer to Section 3.2 for a detailed explanation and Table 1 for a summary of the attributes and their levels):

- **Financial Compensation (FC):** A fixed monthly payment for providing V2G services.
- **Guaranteed Range (GR):** A guaranteed driving range below which the vehicle will never be discharged, in case of emergencies.
- **Minimum Plug-in Time (MP):** A required time that the EV must be plugged in during peak hours (weekdays between 7AM – 7PM); failure to meet the monthly average will result in no financial compensation for that month.
- **Additional Battery Degradation (BD):** An estimated annual battery degradation from participating in V2G above the typical baseline decline of 1–2% annually without V2G.

To provide context, in addition to these four attributes, each contract included two default components. Firstly, by default, the car switches to V2G when connected to a charging point, with users able to enable immediate charging via a complementary phone application. Secondly, the same application displays the number of hours the user's car has been connected during peak hours.

The twelve choice sets were generated using the Ngene software, employing an orthogonal design (Louviere, 2001; Louviere et al., 2000). This design process involved several iterations, carefully checking for dominance[3] in the choice sets. To minimize sequence bias, a randomizer was incorporated into the Qualtrics survey, assigning respondents to one of three different orders of choice-questions. Before finalizing, a pilot test with fifteen participants was conducted. Feedback from the pilot led to improvements in the survey design and clarity of the questions and confirmed that participants varied their choices across the choice-sets.

3.2. V2G contract attributes and levels

This sub-section outlines the rationale and considerations behind the selection of the four contract attributes[4]—Financial Compensation, Guaranteed Range, Minimum Plug-in Time, and Battery Degradation—and their levels (as summarized in Table 1).

Financial compensation (FC) also referred to as remuneration, is widely recognized in the literature as a pivotal component in V2G contracts. It serves to incentivize participants to supply electricity to the grid and compensate for the inconveniences associated with plug-in requirements and battery degradation. This compensation can be fixed or variable. Past studies have predominantly featured fixed payments. For example, Parsons et al. (2014) included annual cashbacks ranging from \$500 to \$5,000, while Geske and Schumann (2018) introduced monthly payment between €15 and €60 and one-time payments from €1,000 to €7,000. Huang et al. (2021) combined a fixed monthly payment (€20 to €100) with variable compensation for additional hours beyond the plug-in obligation (€0 to €0.30 per hour). In contrast, Zonneveld (2019) exclusively incorporated a variable payment structure, stated as compensation per 10 hours.

In this study, we opted for a fixed monthly compensation set at €40, €90, and €140. This decision is motivated by several reasons. First, fixed payments simplify the survey, minimizing mental arithmetic for respondents. Monthly payments are familiar to Dutch residents, who are accustomed to this structure for salaries and other transactions. Moreover, Huang et al. (2021) found that variable

[3] Dominance refers to cases where one contract in a choice set is clearly more favorable than the other, leading to predictable selections and making the data less informative.

[4] To ensure clarity and reduce cognitive load, we excluded several potential contract elements, including contract duration (Kubli et al., 2018; Zonneveld, 2019; Huang et al., 2021); onboard computer capabilities, which influence likelihood of low range when a user enters it (Geske and Schumann, 2018; Kajanova et al., 2022); timing of the next trip (i.e., long or short lead time before entering the vehicle) (Geske and Schumann, 2018); charging speed (Huang et al., 2021); and environmental impact, such as contributions to CO_2 reduction (Parsons et al., 2014).

Table 1
Attributes and their levels.

Attributes	Explanation	Level 1	Level 2	Level 3
Financial Compensation (FC)	A fixed monthly payment for providing V2G services as specified in the contract.	**€40** per month	**€90** per month	**€140** per month
Guaranteed Range (GR)	A guaranteed minimum driving range under which the V2G system will never discharge. This ensures that essential distances can be covered, such as emergency trips to the hospital.	**25** km	**75** km	**125** km
Minimum Plug-in Time (MP)	A minimum time that the EV should be plugged in on weekdays between 7AM-7PM. Financial compensation is contingent on meeting the monthly average requirement; failure to do so will result in no reimbursement for that month.	**2** hours per day	**5** hours per day	**8** hours per day
Battery Degradation (BD)	An additional annual battery degradation caused by participating in V2G. With a typical annual decline without V2G of 1–2%, the contract provides an estimate for the additional degradation caused by V2G. EV batteries are typically replaced when they reach 70–80% of their original capacity.	**1%** per year	**2%** per year	**3%** per year

compensation has a negligible effect on user preferences, which supports our decision to exclude it. Second, these specific compensation amounts were based on estimated potential revenues in the European context, as reported in the literature (Kempton and Tomić, 2005b; White and Zhang, 2011; Hidrue and Parsons, 2015; Noel et al., 2019b). For instance, Noel et al. (2019b) estimated a yearly V2G revenue of €2,000, with a portion allocated to EV owners.

Guaranteed range (GR) is also considered important to compensate for the loss of flexibility, as consistently highlighted in past studies (Parsons et al., 2014; Geske and Schumann, 2018; Kubli et al., 2018; Huang et al., 2021). This attribute ensures a minimum driving distance, below which the EV will never be discharged while participating in V2G. While this range can be expressed in various ways, several studies specify a guaranteed charging level in percentage, either by instructing respondents to use their own EV's range to determine the driving distance or by providing a reference vehicle's total driving range.

In this experiment, the guaranteed range is specified in kilometers, varied in the levels between 25 km, 75 km and 125 km. This approach ensures a uniform context for all respondents, reduces cognitive load by avoiding additional calculations, and is easily understood by both EV and non-EV drivers. The chosen ranges are based on the average commuting distance in the Netherlands, approximately 40 km per day (CBS, 2018; CBS, 2023a). Consequently, the lowest level assesses whether respondents are willing to accept a guaranteed range below the average commute. Moreover, given that practical minimum ranges are unlikely to fall below 20% due to battery degradation considerations, the highest level (125 km) corresponds to a total driving range of 625 km, which is deemed future proof (IEA, 2024a). Importantly, the specific levels are not intended as precise thresholds but span a realistic and policy-relevant range, enabling interpolation to estimate the effect for any value within the interval.

Minimum plug-in time (MP) is also found significant, especially in the early stages of V2G implementation, for ensuring a minimum power capacity and system reliability (Parsons et al., 2014; Huang et al., 2021; Geske and Schumann, 2018). This attribute refers to a contractual agreement for V2G users to keep their vehicles plugged into a charging station for a specified duration. Previous studies have implemented diverse plug-in time restrictions, including daily plug-in times averaged over a month (Parsons et al., 2014; Huang et al., 2021), as well as specific minimum plug-in time per working day, and a minimum number of days per week (with only the former found to be significant) (Geske and Schumann, 2018).

In our design, we introduce a minimum plug-in time, defined as the average number of hours per day that a vehicle must be connected during peak hours (weekdays between 7 AM and 7 PM), with contract levels set at 2, 5, or 8 hours. To allow flexibility, participants must meet this threshold as a monthly average, with the freedom to choose which days and time blocks to plug in—plug-in hours do not need to be contiguous.[5] Failure to meet the average results in no reimbursement for that month. Since V2G is most beneficial during peak commuting hours and periods of high renewable energy generation, only plug-in time within this window are specified and tracked. This design discourages the perception that casual off-peak charging (e.g., overnight) is sufficient, reinforcing the need for active engagement during peak periods.

Battery Degradation (BD) can also pose a significant barrier to V2G adoption. The actual impact of V2G on battery health is still debated. Some studies suggest that V2G may actually improve battery life (Uddin et al., 2018; Wang et al., 2016; Debnath et al., 2014; Ortega-Vazquez, 2014), while others indicate that it might shorten battery life due to increased (dis)charging cycles (Marongiu et al., 2015). Despite these uncertainties, the perception of battery degradation is expected to remain a concern for users (Bakhuis et al., 2025a; Gschwendtner et al., 2021). Battery degradation can be incorporated in various ways. Two previous choice experiments represented it as the amount of additional discharging cycles per session, and its increasing impact on battery health (without specifying that impact) (Zonneveld, 2019; Huang et al., 2021).

In this study, we included battery degradation by expressing it as a percentage of additional degradation, ranging from 1% to 3%, keeping the percentages simple yet realistic. These figures are based on estimations from previous studies (Wang et al., 2016; Guo et al., 2019; Thingvad et al., 2021). In the survey, we also clarify that the typical decline in battery life without V2G is 1–2%, with an EV battery generally requiring replacement when reaching 70–80% of its original capacity. Additionally, the contract specifies that, while the exact impact is uncertain, the provided percentages represent the estimated maximum additional degradation.

[5] This was clarified in the survey instructions (see Appendix C). The design assumes that enforcing strict, contiguous plug-in times would be overly rigid. Instead, system-level stability can be achieved through aggregated user behavior.

3.3. Survey design

The survey was designed to guide participants in making realistic decisions regarding V2G contracts while also gathering additional user characteristics necessary for the final analysis. It was administered in Dutch to ensure clarity and accessibility for the participants, and was organized into four parts: (i) eligibility and introduction, (ii) choice questions, (iii) intentions and attitudes, and (iv) background characteristics.

In the first part, respondents provided informed consent before proceeding to a series of screening questions to confirm their eligibility: holding a valid driver's license, residing in the Netherlands, and having regular access to a car—whether owned, leased, rented, or shared. Only those meeting all criteria could proceed. Respondents then answered quota-based questions on age, gender identity, education level, and type of car predominantly driven (battery electric, hybrid electric, or fossil fuel) to ensure sample diversity and approximate representativeness. Participants also indicated their familiarity with V2G on a five-point scale. Finally, they were given a brief introduction to the V2G innovation, outlining its bi-directional charging capabilities, its role in supporting electricity grid flexibility, and the potential financial compensation available to participants.

The second part contained the V2G choice experiment. Before the twelve choice sets were presented sequentially, the survey set-up was explained, including the structure of the V2G contracts and their defining attributes. To familiarize participants, an example choice set featuring two hypothetical V2G contracts was shown (see Fig. 1). To further support comprehension, extended explanations of the contract elements and their broader context were provided—either upfront or via pop-up windows embedded within each question. In each choice set, respondents were instructed to choose their preferred option (A or B) based on varying attribute levels. Following each choice, they were also asked whether they would accept the selected contract if it were actually offered (Yes or No). See Appendix C for the full V2G introduction and attribute descriptions shown to respondents.

The third part captured participants' stated intentions by asking about their likelihood of participating in V2G, key motivators (or drivers) for doing so, and perceived barriers to adoption. In addition, respondents were asked to state their attitudes towards new technologies, the importance of environmental sustainability in their decision-making, and their perception of their car's role in providing freedom and mobility. Most of these questions used a five-point scale, ranging from "very unlikely" to "very likely", with a neutral midpoint.

The fourth part collected detailed information on background characteristics, including socio-demographic (e.g., age, education), household (e.g., size, housing type), and car usage factors (e.g., vehicle type, commuting frequency).

3.4. Data collection

Data collection was conducted in the Netherlands during September and October 2023 using the online Qualtrics platform. Respondents took an average of nine minutes to complete the survey. The final dataset consists of 1,018 responses: 900 were recruited through a professional panel provider (Dynata[6]) and 118 through the authors' networks.

Given our target population—adult car drivers in the Netherlands—direct benchmarking is limited. However, to support robust preference estimation and generate policy-relevant insights for broader V2G adoption, we ensured sample diversity. Accordingly, quota sampling was applied for gender, age, education, and car type, using CBS data where available. Table 2 presents summary statistics for the quota variables; full sample statistics of all variables are provided in Table A1 in Appendix A.

The final sample features a slightly more balanced gender distribution (53% male, 47% female) than the license-holding population, which skews more male (CBS, 2013; CBS, 2019). Age distributions closely reflect those of car users in the Netherlands (CBS, 2025a), while education levels are somewhat higher than in the general population (54% with a Bachelor's degree or above vs. ~33% nationally) (CBS, 2025b). Electric and hybrid vehicle users were intentionally oversampled (29%) relative to their national share (~17.5%) to enable meaningful subgroup analysis (CBS, 2025a).

Regarding the sample size, while no strict minimum applies to discrete choice experiments, common guidelines recommend at least 100 respondents to ensure reliable estimates (Pearmain and Kroes, 1990; de Bekker-Grob et al., 2015). A more formal rule by Johnson and Orme (2003) suggests a minimum of 83 respondents for our specific design.[7] Our final sample of 1,018 comfortably exceeds these thresholds.

4. Methods

In this study, we employ the choice modeling methodology, known for its efficacy in unraveling user preferences in hypothetical scenarios and providing a robust framework for probing decision-making processes. While the multinomial logit model (MNL) is among the simplest and most widely used random utility models (McFadden, 1981; Ben-Akiva, 1985; Bierlaire, 1998), it has limitations in accounting for unobserved heterogeneity (Wen and Lai, 2010). To overcome this, we adopted a latent class choice model

[6] Dynata is a global market research company that provides a comprehensive platform for data-driven insights, offering access to a diverse panel of participants for conducting surveys and collecting valuable consumer data; they pay respondents for survey participation and emphasize checking for representativeness in their datasets.

[7] According to Johnson and Orme (2003), the minimum sample size can be calculated using the formula: $n \geq ((500 \bullet c) / (t \bullet a))$, where c is the maximum number of levels for any attribute, t is the number of choice tasks per respondent, and a is the number of alternatives per task. For our design ($c = 4$, $t = 12$, $a = 2$), this results in a recommended minimum of 83 respondents.

Contract Elements	Contract Options	
	V2G Contract A	V2G Contract B
Financial Compensation	**€40,-** *per month*	**€140,-** *per month*
Guaranteed Range	**75** *km*	**75** *km*
Minimum Plug-in Time Working days between 7am and 7pm	**2** *hours per day*	**8** *hours per day*
Extra Battery Degradation	**2%** *per year*	**1%** *per year*

Fig. 1. Example of a choice set in the survey (translated from Dutch).

Table 2
Summary statistics of selected variables (n = 1,018).*

Variable	Categories	Percentage of respondents
Gender	Male	53%
	Female	47%
	Other	0%
Age	18 – 24	4%
	25 – 30	9%
	31 – 40	17%
	41 – 50	17%
	51 – 60	19%
	61 – 65	10%
	> 65	24%
Education**	Primary school	1%
	VMBO or MAVO	15%
	HAVO or VWO	7%
	Secondary vocational education (MBO)	23%
	Bachelor of applied science (HBO)	28%
	Bachelor of science	6%
	Master of science or higher	20%
Vehicle type	Full Electric	11%
	Hybrid	18%
	Fossil	71%
V2G familiarity	Never heard of it before	63%
	Heard of it, but not well known	19%
	Somewhat familiar	11%
	Fairly familiar	3%
	Very familiar	4%

* For full summary statistics of all variables, see Table A1 in Appendix A.
** VMBO and MAVO are lower levels of secondary education; HAVO and VWO are higher levels.

(LCCM), which is a well-established choice modeling methodology (Thorhauge et al., 2021).

4.1. Latent class model

The latent class model stands out as a robust approach well-suited for capturing unobserved heterogeneity in the data (Behnood et al., 2014, Cerwick et al., 2014, Shaheed and Gkritza, 2014, Yasmin et al., 2014; Thorhauge et al., 2021; Liao et al., 2020). In contrast to the widely used random parameters models with continuous mixing distributions, such as the mixed logit model,[8] latent class models eliminate the need for analysts to make distributional assumptions to capture unobserved heterogeneity (Wen and Lai, 2010; Hess et al., 2008; Xiong and Mannering, 2013). Instead, latent class models identify homogeneous subgroups within the data, operating under the assumption that there are underlying, unobservable discrete classes within the population, and that each individual belongs to one of these classes.

[8] Mixed logit is more flexible as it allows the parameters associated with observed variables for each individual to vary across a known population distribution (Shen, 2014). However, the nature of this distribution has to be assumed. In essence, latent class simplifies by assuming fixed classes, while mixed logit accommodates a more flexible distribution but with added assumptions. The drawback is that the number of classes is usually small so there is a coarse approximation of the distribution of heterogeneity (Behnood et al., 2014).

In essence, this latent class approach allows us to categorize the experiment participants into a finite number of distinct groups (or latent classes), effectively capturing class-specific unobserved heterogeneity without relying on distributional assumptions. It assumes that each class has a unique set of parameters (Swait, 1994; Boxall & Adamowicz, 2002), and that respondents are probabilistically assigned to different classes. This means that each individual has a certain probability of belonging to each of the specified latent classes. By capturing heterogeneity in this manner, the model can predict class memberships by using additional independent variables, including less obvious ones, such as psychometric factors.

In our experiment, participants chose between two unlabeled contracts (A and B), each defined by four attributes. For each latent class x, a distinct set of attribute effects (β_{xk}) is estimated, where k denotes each attribute. In addition, the class membership model estimates an intercept[9] (γ_{x0}) and a set of regression coefficients (γ_{xr}) for each class. These coefficients are associated with covariates $\boldsymbol{r}$, representing user characteristic factors, which serve as indicator variables to explain the likelihood of belonging to a particular class. Latent class models can be estimated using maximum likelihood procedures. For a detailed explanation of the underlying equations, see Appendix B. For more information on the model structure and estimation process, refer to Greene and Hensher (2003) and Shen (2014).

In terms of interpretation, the sign of each estimated attribute coefficient (β_{xk}) indicates whether the attribute has a positive or negative impact on utility, while its magnitude reflects the strength of that effect. For example, a positive estimate for financial compensation (β_{xFC}) indicates that higher compensation increases contract utility for users in class x. For the covariates (γ_{xr}), the sign of each estimate indicates whether individuals with that characteristic are more or less likely to belong to a particular class. For instance, a negative estimate for the gender indicator ($\gamma_{xGender}$) suggests that females are less likely than males to belong to class x. The t-statistic reflects statistical significance of the estimate, with higher absolute values suggesting greater significance, and the sign corresponding to the direction of the effect.

4.2. Model development and estimation

Initially, a multinomial logit model was estimated to evaluate whether the data gave sensible results and establish a baseline for comparison with the latent class model. Subsequently, to capture unobserved heterogeneity across individual observations (Wen and Lai, 2010), the latent class choice model was developed (Hess, 2014).

The model fit can be evaluated by comparing models using information criteria, such as the Akaike's Information Criteria (AIC) (Akaike, 1974) or Bayesian Information Criteria (BIC) (Schwarz, 1978). A low value of AIC and BIC is preferred as it indicates a balanced trade-off between model fit and parsimony (Lanza et al., 2007). For latent class analysis, the BIC is favored for its robust performance, primarily due to its more stringent penalty on the number of parameters (Walker and Li, 2007; Wen and Lai, 2010). In addition to a low BIC value, it is crucial that none of the class sizes is trivial (>5% sample size) (Nasserinejad et al., 2017), and they should be distinguishable with meaningful labels based on expressed heterogeneity. Hence, the final selection of the number of classes is based on comparing models with the lowest local minima of BIC values, ensuring non-trivial class sizes, and checking for interpretability of the classes.

An overview of the fit of successive model runs is provided in Table 3, spanning from a single class (corresponding to a multinomial logit model) to ten classes, initially excluding covariates. The model estimations were performed using Latent Gold software (Vermunt and Magidson, 2005; Vermunt and Magidson, 2021). Analyzing the trends in Table 3, the BIC exhibits a steep decrease up to four classes, indicating that the latent class choice model is statistically superior to the multinomial logit model. The BIC then declines at a slower rate up to seven classes, after which it starts increasing.

To determine the optimal number of classes, we compared models with three, four, and five classes. The four-class model outperformed the three-class model on BIC and interpretability while maintaining non-trivial class sizes. Conversely, increasing to five or more classes presented challenges in terms of interpretability and maintaining adequate class sizes. After testing these models with preliminary covariates, the four-class model remained interpretable and maintained a low BIC. Consequently, the four-class model was selected for further analysis.

Upon determining the optimal number of classes, we further developed the model by iteratively incorporating statistically significant covariates. As noted, these covariates reflect user characteristics—encompassing socio-demographic, car use, household, and preference and attitude factors—which were derived from the survey data. The final model included 31 covariates that were statistically significant in at least one class, each with a p-value below 0.10. This enables us to identify which societal sub-groups have specific preferences regarding V2G adoption (i.e., class membership).

Once the model was finalized, we assessed the relative importance of each attribute within each class. Following the approach outlined by Vermunt and Magidson (2005) and Araghi et al. (2016), we first calculated the utility range for each attribute—the difference between its highest and lowest utility levels—within each class, based on the estimated coefficients. To determine the relative importance percentage (RI%) of each attribute, we divided its utility range by the sum of the utility ranges for all attributes in that class. This RI% represents each attribute's contribution to the overall utility of the class. By calculating these percentages, we gained a clearer understanding of the varying priorities across the classes and identified the most influential attributes, which guided the naming and characterization of the distinct classes.

The structure of the latent class model is visually represented in Fig. 2. Essentially, the analysis identified four latent classes, each

[9] The intercepts for each latent class represent the estimated mean preference for V2G attributes when all user characteristics are at their reference levels. They serve as baselines, with deviations captured by the coefficients of the predictor variables.

Table 3
Model fit of the latent class models, excluding covariates, from the Latent Gold software.

Number of classes	Number of parameters	Degrees of freedom	Log-likelihood at convergence	Akaike's information criterion (AIC)	Bayesian information criterion (BIC)
1	4	1,014	−7,570.2	15,148.4	15,168.1
2	9	1,009	−6,813.3	13,644.5	13,688.9
3	14	1,004	−6,559.5	13,146.9	13,215.9
4	19	999	−6,417.4	12,872.8	12,966.4
5	24	994	−6,377.9	12,803.8	12,922.1
6	29	989	−6,339.6	12,737.3	12,880.1
7	34	984	−6,315.6	12,699.2	12,866.7
8	39	979	−6,300.2	12,678.4	12,870.5
9	44	974	−6,295.5	12,678.9	12,895.7
10	49	969	−6,283.8	12,665.6	12,906.9

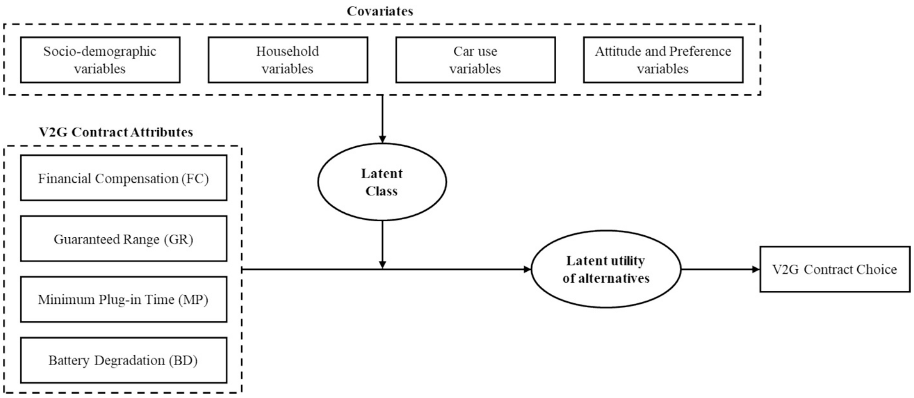

Fig. 2. Graphical representation of the latent class model with covariates.

distinguished by V2G contract attribute estimates that reflect the impact on utility and relative importance of these attributes for individuals within each class. Additionally, class membership is evaluated based on covariates (user characteristics), represented by indicator variables derived from the survey data.

5. Results

The summary statistics for the variables used in the final 4-class latent class choice model are presented in Table 4. The results of the final model estimation—assessing user preferences towards V2G—are presented in Table 5. This section first outlines contract acceptance rates, then provides an overview of class profiles, and highlights select findings across all classes. While not a central focus, willingness to pay (WTP) estimates are provided for interested readers in Appendix E (see Table E1).

5.1. Contract acceptance

The contract acceptance analysis reflects the respondents' willingness to accept their chosen contract in each choice set if it were actually offered. As shown in Fig. 3, the overall acceptance rate is 53%, with relatively modest variation across the four latent classes[10]; Classes 2 and 4 exhibit slightly higher acceptance rates (60% and 64%) compared to Classes 1 and 3 (48% and 46%), though the differences are minor. Moreover, acceptance levels are fairly consistent across the twelve choice tasks (see Appendix D, including Table D1 and Figures D1–D10, for a detailed breakdown by choice set). In cases where class differences are observed, they align closely with the latent class model. For example, financially motivated respondents (Class 4) are more likely to accept contracts offering higher compensation, reflecting their emphasis on monetary incentives.

5.2. Latent class profiles

The profiles described in this section outline four distinct user segments identified by the latent class model, each defined by unique attribute preferences and respondent characteristics. A summary of these latent preference profiles is provided in Table F1 in

[10] Class-specific acceptance rates were calculated using posterior class membership probabilities derived from *Latent GOLD*—a probabilistic assignment of respondents to classes based on their choice behavior.

Table 4
Summary statistics for variables included in the final model estimation.

Variable description	Mean (%)	Standard deviation
Socio-demographic factors		
Gender Indicator *(1 if identifies as female; 0 otherwise)*	47%	0.50
Young Age Indicator *(1 if age is between 18 and 24; 0 otherwise)*	4%	0.19
Mature Age Indicator *(1 if age is above 65; 0 otherwise)*	24%	0.42
Lower Education Indicator *(1 if completed high school or lower; 0 otherwise)*	23%	0.42
Higher Education Indicator *(1 if completed a master's degree or higher; 0 otherwise)*	20%	0.40
Lower Income Indicator *(1 if household annual income before taxes is €60.000 or lower; 0 otherwise)*	63%	0.48
Employment Indicator *(1 if works part-time (up to 32 h) or full-time (more than 32 h); 0 otherwise)*	61%	0.49
Household factors		
Household Size Indicator *(1 if household consists of four persons or more; 0 otherwise)*	21%	0.41
Household Composition Indicator *(1 if lives with a partner without children; 0 otherwise)*	42%	0.49
Children Indicator *(1 if has three or more children under 18 in the household; 0 otherwise)*	4%	0.19
Living Area Indicator *(1 if lives in a rural area; 0 otherwise)*	29%	0.46
Parking Access Indicator* *(1 if has access to parking—private driveway or garage—at home; 0 otherwise)*	60%	0.49
Renewable Energy Use Indicator *(1 if uses renewable energy sources at home; 0 otherwise)*	48%	0.50
Lower Electricity Bill Indicator *(1 if monthly electricity bill is €100.- or less on average; 0 otherwise)*	53%	0.50
Car use factors		
Car Type Indicator – Fossil Fuel *(1 if predominately drives a fossil-fuel vehicle; 0 otherwise)*	71%	0.46
Car Access Indicator – Ownership *(1 if owns their car(s); 0 otherwise)*	88%	0.33
Car Access Indicator – Private Leasing *(1 if privately leases their car(s); 0 otherwise)*	11%	0.32
Car Access Indicator – Sharing *(1 if does car sharing; 0 otherwise)*	11%	0.32
Remote Working Indicator *(1 if never works from home; 0 otherwise)*	55%	0.50
Driving Frequency Indicator *(1 if drives 3 days per month or less; 0 otherwise)*	14%	0.35
Car Use Type Indicator – Commute *(1 if uses their car 5 days or more per week for commuting; 0 otherwise)*	27%	0.44
Car Use Type Indicator – Errands *(1 if uses their car 5 days or more per week for errands; 0 otherwise)*	16%	0.36
Car Use Type Indicator – Leisure *(1 if uses their car 5 days or more per week for leisure activities; 0 otherwise)*	16%	0.37
Long Journey Frequency Indicator *(1 if uses their car two times or less per month for journeys longer than 50 km; 0 otherwise)*	52%	0.50
Preference and attitude factors		
V2G Familiarity Indicator *(1 if never heard of V2G; 0 otherwise)*	63%	0.48
V2G Participation Likelihood Indicator *(1 if 'very likely' to participate in a V2G program if it were available; 0 otherwise)*	11%	0.31
Car Attachment Indicator *(1 if finds their car 'very important' for freedom and mobility; 0 otherwise)*	43%	0.50
Environmental Importance Indicator *(1 if considers environmental sustainability 'very important' in decision-making; 0 otherwise)*	18%	0.38
Technology Enthusiasm Indicator *(1 if has a 'very reserved' attitude towards using new technologies; 0 otherwise)*	3%	0.17
EV Concern Indicator – Driving Range *(1 if generally concerned about the range of electric vehicles; 0 otherwise)*	58%	0.50
EV Concern Indicator – Initial Costs *(1 if generally concerned about the initial costs of electric vehicles; 0 otherwise)*	51%	0.50

* Access to home parking is included as a separate variable, as V2G remains viable even without home charging. While private parking—and the ability to charge at home—can significantly support EV and V2G adoption, it is not strictly required. Depending on the implementation, users without home chargers could still participate via semi-public or public charging (e.g., at workplaces or nearby residences). Capturing their preferences is important for evaluating the scalability and viability of V2G systems.

Appendix F.

5.2.1. Class 1: Range-Focused and Finance-Disregarding users

The first and largest group, comprising 43% of the total sample, is labeled '*Range-Focused and Finance-Disregarding Users*.' As the name suggests, these respondents prioritize the guaranteed range attribute, with a relative importance of 66%. The remaining attributes are found less important, with minimum plug-in time at 12% and battery degradation at 13%, while financial compensation is the least important at just 9%—the lowest across all classes. Uniquely, and contrary to the expectations, this class shows a negative estimate for financial compensation. Several factors may help explain this pattern.[11] First, additional analysis using discrete levels for compensation (€40, €90, €140) reveals a clear non-linear response: utility peaks at €40, but drops at higher levels, indicating that payments beyond a certain level (e.g., €40) may be perceived as excessive or as a signal of inconvenience or hidden trade-offs. Second, this aligns with findings from a complementary study on stated intentions (Bakhuis et al., 2025b), which shows that individuals with characteristics typical of this group tend to prioritize environmental or grid-related motivations over financial incentives for V2G participation. Third, the stark contrast in attribute weights suggests that users in this class heavily prioritize range, substantially reducing sensitivity to monetary incentives.

Examining class membership, we observe that individuals in this class are more likely to be female, older (above 65 years old), employed, mainly driving fossil fuel vehicles, engaging in frequent commuting (5+ days per week), and using renewable energy sources, such as solar PV, at home. Conversely, respondents expressing a likelihood to adopt V2G if it were available to them are less likely to belong to this class.

5.2.2. Class 2: Range-Focused and plug-in Time-Disregarding users

The second-largest group, constituting 29% of the total sample, is labeled '*Range-Focused and Plug-in Time-Disregarding Users*.' In this group, respondents place minimal importance on minimum plug-in time, assigning it just 9% relative importance, while their preferences are more evenly distributed across the other attributes. Similar to Class 1, guaranteed range remains their top priority at 45% relative importance, but they also place significant value on financial compensation and battery degradation, each at 23%. Hence, while their main concern is securing a high guaranteed range, they also prioritize financial compensation and battery health. Notably, this group places the highest emphasis on battery degradation compared to other classes and assigns the second-highest value to financial compensation.

Examining class membership, respondents who are more likely to belong to this class include younger males (aged 18 to 24), those with at least a high school diploma, respondents with lower income (€60,000 annually or lower), individuals living with a partner without children, those residing in rural areas, car owners, private leasers and sharers, as well as respondents who frequently use their car for leisure activities (5+ days per week). Conversely, individuals who never engage in remote work or those unfamiliar with V2G are less likely to belong to this class.

5.2.3. Class 3: Flexibility-Focused users

The third group, representing 18% of the total sample, is labeled '*Flexibility-Focused Users*.' These respondents prioritize flexibility, placing the greatest relative importance on minimizing plug-in time (53%) and ensuring a sufficient guaranteed range (25%). This suggests that they highly value the ability to use their car at any time without compromising driving range. Similar to the two biggest classes, guaranteed range remains important. Additionally, financial compensation and battery degradation are given lower but equal importance, both at 11%. Overall, this group focuses primarily on flexibility, with less concern for financial compensation or battery health.

Examining class membership, higher educated individuals with at least a master's degree, higher income (€60,000 or higher annually), those without access to private parking, those who drive relatively frequently (>3 days per month generally and 5+ days per week for errands) or sometimes embark on long journeys (>2 times per month), those unfamiliar with V2G, and those who express concerns about EV driving range are more likely to belong to this class. On the contrary, individuals from larger households (at least four persons), living with a partner and children, who own their car(s), participate in car-sharing programs, prioritize environmental sustainability in their decision-making, and express concerns about the initial costs of EVs are less likely to be part of this class.

5.2.4. Class 4: Finance-Focused and Range-Disregarding users

The fourth and smallest group, with 10% of the total sample, is labeled '*Finance-Focused and Range-Disregarding Users*.' These respondents distinctly prioritize financial compensation, with a relative importance of 70%. This suggests that financial incentives are their primary consideration when selecting V2G contracts. Besides financial compensation, they also place notable emphasis on

[11] This pattern does not appear to reflect poor response quality. Completion times were within acceptable bounds, no straight-lining behavior (i.e., selecting the same response across many or all choice tasks) was detected, and the survey was pilot-tested and refined to ensure clarity, realistic trade-offs, and balanced choice tasks.

Table 5
Latent class choice model (LCCM) on user preferences toward the vehicle-to-grid (V2G) innovation in the Netherlands.

Classes	**Class 1 (43%)** *Range-Focused and Finance-Disregarding Users*			**Class 2 (29%)** *Range-Focused and Plug-in Time-Disregarding Users*			**Class 3 (18%)** *Flexibility-Focused Users*			**Class 4 (10%)** *Finance-Focused and Range-Disregarding Users*		
Attributes (β)												
	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%
β_{FC} *(Financial Compensation)*	−0.005	−4.78	9%	0.004	3.50	23%	0.007	2.94	11%	0.037	9.63	70%
β_{GR} *(Guaranteed Range)*	0.04	19.37	66%	0.01	6.56	45%	0.02	6.48	25%	0.001	0.46	2%
β_{MP} *(Minimum Plug-in Time)*	−0.11	−6.93	12%	−0.02	−1.99	9%	−0.58	−15.74	53%	−0.18	−5.97	20%
β_{BD} *(Battery Degradation)*	−0.33	−5.22	13%	−0.18	−4.04	23%	−0.36	−3.83	11%	−0.22	−1.80	8%
Covariates (γ)												
γ_{x0} *(Intercept)*	0.95	2.31		1.58	3.14		−2.21	−2.61		−0.32	−0.57	
Socio-demographic factors												
Gender Indicator* *(female)*	0.09	1.52		−0.18	−2.22		–	–		–	–	
Young Age Indicator *(18 – 24 years)*	–**	–		0.56	2.50		–	–		–	–	
Mature Age Indicator *(> 65 years)*	0.16	1.78		–	–		–	–		–	–	
Lower Education Indicator *(≤ high school diploma)*	–	–		−0.18	−1.77		–	–		–	–	
Higher Education Indicator *(≥ master's degree)*	–	–		–	–		0.26	2.34		–	–	
Employment Indicator *(employed part- or full-time)*	0.20	2.35		–	–		–	–		–	–	
Lower Income Indicator *(≤ €60.000/year)*	–	–		0.18	1.92		−0.22	−2.22		–	–	
Household factors												
Household Size Indicator *(≥ 4 persons)*	–	–		–	–		−0.19	−1.52		–	–	
Household Composition Indicator *(partner, no children)*	–	–		0.15	1.63		−0.25	−2.63		–	–	
Children Indicator *(≥ 3 children)*	–	–		–	–		–	–		0.71	2.68	
Living Area Indicator *(rural area)*	–	–		0.19	2.18		–	–		–	–	
Parking Access Indicator *(has private parking access)*	–	–		–	–		−0.25	−2.90		0.16	1.60	
Renewable Energy Use Indicator *(uses renewables)*	0.11	1.83		–	–		–	–		−0.21	−2.13	
Lower Electricity Bill Indicator *(≤ €100/month)*	−0.09	−1.51		−0.15	−1.90		0.16	1.84		–	–	
Car use factors												
Car Type Indicator – Fossil Fuel	0.12	1.77		–	–		–	–		−0.15	−1.43	
Car Access Type Indicator – Ownership	–	–		0.48	3.21		−0.28	−2.02		–	–	
Car Access Type Indicator – Private Leasing	−0.19	−1.52		0.53	3.57		–	–		–	–	
Car Access Type Indicator – Sharing	–	–		0.49	3.50		−0.76	−2.87		–	–	
Remote Working Indicator *(never works from home)*	–	–		−0.20	−2.11		–	–		–	–	
Driving Frequency Indicator *(≤ 3 days/month)*	–	–		–	–		−0.22	−1.54		–	–	
Car Use Type Indicator – Commute *(≥ 5 days/week)*	0.21	2.69		–	–		–	–		–	–	
Car Use Type Indicator – Errands *(≥ 5 days/week)*	0.16	1.44		–	–		0.25	1.64		−0.50	−2.22	
Car Use Type Indicator – Leisure *(≥ 5 days/week)*	–	–		0.27	2.18		–	–		–	–	
Long Journey Frequency Indicator *(≤ 2 times/month)*	–	–		0.13	1.48		−0.19	−2.10		–	–	
Preference and attitude factors												
V2G Familiarity Indicator *(never heard of it)*	–	–		−0.27	−3.10		0.16	1.66		–	–	
V2G Participation Likelihood Indicator *(very likely)*	−0.21	−3.31		–	–		–	–		0.26	2.59	
Car Attachment Indicator *(very attached)*	–	–		–	–		0.13	1.49		−0.17	−1.72	
Environmental Importance Indicator *(very important)*	–	–		–	–		−0.19	−1.58		–	–	

(*continued on next page*)

Table 5 (*continued*)

Classes	Class 1 (43%) *Range-Focused and Finance-Disregarding Users*			Class 2 (29%) *Range-Focused and Plug-in Time-Disregarding Users*			Class 3 (18%) *Flexibility-Focused Users*			Class 4 (10%) *Finance-Focused and Range-Disregarding Users*		
Attributes (β)												
	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%	Estimate	t-stat.	RI%
Technology Enthusiasm Indicator *(very reserved)*	–	–		–	–		–	–		0.40	1.85	
EV Concern Indicator – Driving Range	–	–		–	–		0.24	2.35		−0.20	−1.85	
EV Concern Indicator – Initial Costs	–	–		–	–		−0.23	−2.41		0.26	2.48	
Model fit												
LL *(start)*	−8,467.49											
LL *(final)*	−6,275.50											
BIC	13,326.67											
AIC	12,774.99											
Entropy R^2	0.8173											
Standard R^2	0.8098											
Number of parameters	112											
Number of respondents	1,018											
Number of observations	12,216											
Prediction error	21.5 %											

* For a full description of the indicator variable, refer to the corresponding variable in Table 4.
** Cells marked with '–' indicate variables that were not statistically significant and are therefore excluded from the table for clarity.

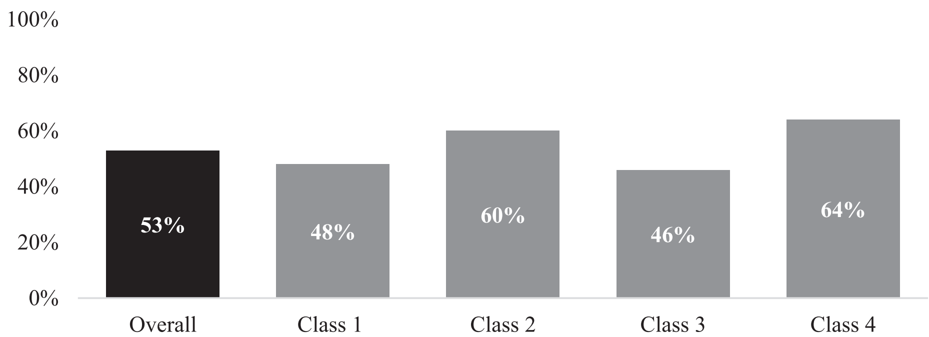

Fig. 3. Average contract acceptance rates across the full sample and by latent class.

minimum plug-in time, followed by battery degradation, with relative importance values of 20% and 8%, respectively. In contrast, they disregard guaranteed range in their decision-making, which holds just 2% relative importance and is not statistically significant. Thus, it can be speculated that financial compensation may offset their aversion towards plug-in time and battery degradation. Notably, plug-in time holds the second-highest relative importance in this class compared to the others, surpassed only by Class 3.

Examining class membership, individuals with three or more children in the household, those with access to private parking, those unfamiliar with V2G, those likely to participate in V2G if it were available, those with a reserved attitude toward new technologies, and those concerned about the initial costs of EVs are more likely to belong to this class. In contrast, individuals who use their cars frequently for errands (5+ days per week), are deeply attached to their cars for freedom and mobility, are concerned about EV range, and use renewable energy at home are less likely to belong to this class.

5.3. Select findings

5.3.1. Attribute estimates

The analysis reveals that guaranteed range receives the highest relative weight within the two largest user groups, which together account for 72% of respondents. In contrast, financial compensation is only the most influential attribute within the smallest group (10% of respondents), and is assigned relatively less weight in the other classes. Minimum plug-in time emerges as the top priority only for the third group (18% of respondents), while playing a less prominent role in the remaining classes. Battery degradation is consistently regarded as less critical across all classes—never receiving the highest weight—but sees its greatest relative importance in Class 2 (27% of respondents). Notably, in the three larger classes, financial compensation and battery degradation receive similar relative weights and consistently rank as the two lowest or joint-lowest attributes.

5.3.2. Class membership

5.3.2.1. Socio-demographic factors. Socio-demographic factors play a significant role in class membership. Gender is an important factor, with females more likely to belong to Class 1 and less likely to Class 2, suggesting that they prioritize guaranteed range and place less emphasis on financial compensation and battery degradation. This aligns with research indicating that females tend to be more sensitive to range anxiety (Caperello et al., 2014; Abay and Mannering, 2016). Similarly, older individuals (65 years and above) are also more likely to fall into Class 1, which prioritizes guaranteed range, likely due to a traditional outlook on vehicle ownership and a higher aversion to new technologies (Charness and Boot, 2009; Schoettle and Sivak, 2014), potentially exacerbated by lower digital literacy, for instance, to use the 'immediate charge' functionality.

In contrast, younger individuals (ages 18 to 24) are more likely to be in Class 2, demonstrating minimal concern for plug-in time, possibly due to more flexible mobility patterns (Haustein and Siren, 2015; Levin, 2019; Casadó et al., 2020). Education and income also influence class membership, with higher educated (master's degree or above) and higher income (earning above €60,000 annually) respondents both more likely to be in Class 3, prioritizing guaranteed range and plug-in time. This reflects the flexibility typically sought by higher-educated individuals (Ye and Titheridge, 2017; Erhardt et al., 2019), while higher income seems to reduce the focus on financial compensation (Heckman et al., 2018; Autor and Handel, 2013). Lastly, employed individuals—especially those with frequent commutes—are more likely to belong to Class 1, prioritizing guaranteed range and relatively disregarding financial compensation.

5.3.2.2. Household factors. Household factors also significantly shape V2G preferences. Respondents living with a partner but without children are more likely to belong to Class 2 and less likely in Class 3, indicating less concern for plug-in times, likely due to fewer responsibilities and greater adaptability (Stradling et al., 2007; McDonald, 2008). Respondents from larger households (four or more people) are also less likely to be in Class 3, while those with three or more children are more likely to belong to Class 4. This suggests a prioritization of financial compensation over flexibility, likely driven by higher living expenses associated with childcare (Chatterjee and Scheiner, 2015; Clark et al., 2016; Piotrowska et al., 2023; Thomson et al., 2023).

Living area also influences preferences. Rural residents are more likely to be in Class 2, relatively disregarding plug-in times, likely due to longer commutes and less sporadic schedules, making guaranteed range a priority (Kim and Ulfarsson, 2008). Those with private parking are less likely to be in Class 3, which places less emphasis on flexibility-related attributes, likely because convenient home charging reduces flexibility concerns related to range and plug-in time (Pearre et al., 2011; Ge et al., 2021; Hardman et al., 2018). Finally, respondents using renewable energy at home, are more likely to belong to Class 1 and less likely to fall into Class 4, disregarding financial compensation, likely due to their environmentally conscious mindset (Sovacool et al., 2018a; Axsen and Kurani, 2013).

5.3.2.3. Car use factors. Car use factors reveal important distinctions among V2G user classes. Respondents primarily driving fossil fuel vehicles are more likely to belong to Class 1, highly valuing guaranteed range. This may reflect greater range anxiety, as these drivers are accustomed to larger ranges and quicker refuelling (Franke and Krems, 2013a; 2013b; Nilsson, 2011). In contrast, research shows that individuals with EV experience generally display less range anxiety (Rauh et al., 2015; Schäuble et al., 2017; Neaimeh et al., 2017; Jensen et al., 2013).

Considering car access type, car owners and private leasers are more likely to be in Class 2 and less likely in Class 1 or Class 3, indicating a greater emphasis on financial compensation and battery degradation. This may be linked to their personal stake in the vehicle's condition (Rezvani et al., 2015; Neubauer and Wood, 2014). Similarly, car sharers are more likely to belong to Class 2 and less likely in Class 3, suggesting less concern for plug-in time, likely due to their familiarity with trip planning. Furthermore, financial and range considerations remain important factors for car sharers (Wielinski et al., 2017; Jin et al., 2020; Gschwendtner and Krauss, 2022).

Regarding commute patterns, non-remote workers are less likely to be in Class 2, likely because peak-hour plug-in times are less of a concern, as their cars remain parked at work (Lyons and Chatterjee, 2008). Furthermore, frequent car users for commuting and errands (5+ days per week) are more likely to belong to Class 1, prioritizing guaranteed range, while infrequent drivers ($\leq$3 days per month) are less likely to be in Class 3, indicating lower flexibility needs. Lastly, the model shows that frequent errand drivers are more likely in Class 3, while frequent leisure drivers are more likely in Class 2; leisure drivers likely care less about plug-in time because they can schedule travel more flexibly.

5.3.2.4. Preference and attitude factors. Preference and attitude factors also offer key insights into V2G class membership. Respondents indicating to be likely to participate in V2G tend to belong to Class 4 and are less likely in Class 1. This indicates that financial compensation is a primary motivator for participation, while range concerns are a notable predictor of lower likelihood of participation. Respondents unfamiliar with V2G are more likely in Class 3 and less likely in Class 2, reflecting a high emphasis on minimizing plug-in time. This may indicate an overestimation of the inconvenience of plug-in times among unfamiliar respondents, possibly due to a lack of understanding of features such as the immediate charge button.

Car attachment also influences preferences. Individuals who view their cars as symbols of freedom are more likely in Class 3, valuing flexibility over financial compensation. Conversely, those with a reserved attitude toward using new technologies are more likely to fall into Class 4, possibly requiring high financial incentives. Lastly, the findings highlight that general concerns about EVs align with V2G contract preferences: individuals worried about EV range are more likely to belong to Class 3 (emphasizing guaranteed range and plug-in time), while those concerned about the initial costs of EVs are more likely in Class 4 (primarily valuing financial compensation).

6. Practical implications

The forthcoming section provides practical implications derived from the study. First, the results of this research are compared with existing literature. Then, we discuss the policy implications and general recommendations.

6.1. Parameter estimates: Comparison with literature

Regarding financial compensation (FC), this study presents a more nuanced picture of V2G preferences than prior research, which typically reports strong positive effects of financial incentives on adoption (Huang et al., 2021; Parsons et al., 2014; Zonneveld, 2019). While compensation is clearly important for some—particularly in Class 4 (10% of respondents), where it is the dominant factor—it is not universally prioritized. In fact, for Classes 1 and 3, together representing 61% of respondents, financial compensation holds the lowest relative importance among all assessed attributes. While this may appear counterintuitive, our findings indicate that many users place substantial value on non-financial motivations when considering V2G adoption. Stated intention data show that although financial incentives received the highest average rating (M = 3.59 out of 5), electricity grid benefits (M = 3.47) and environmental motivations (M = 3.37) followed closely—with many users prioritizing these non-financial factors (Bakhuis et al., 2025b). These patterns likely reflect growing public awareness in the Netherlands of climate change and grid congestion, both of which are increasingly prominent in policy and public discourse (CBS, 2023b; TenneT, 2023; IEA, 2024b, 2025). Overall, our results lend partial support to Geske and Schumann's (2018) argument that reducing participation burdens—particularly those related to range and reliability—can support V2G adoption, even in the absence of strong financial incentives.

Regarding guaranteed range (GR), the study reveals that most respondents place the highest value on it compared to other attributes. It is the top priority for Class 1 and Class 2, which together represents 72% of respondents, and the second most important for Class 3 (18% of respondents), meaning that 90% of respondents value it highly. This aligns with previous research highlighting a strong positive impact of guaranteed range on the willingness to participate in V2G (Huang et al., 2021; Geske and Schumann, 2018; Kubli et al., 2018; Noel et al., 2019b; Parsons et al., 2014; Zonneveld, 2019). However, this study adds nuance by identifying a segment (10% in Class 4) that shows no concern for it at all. The high valuation of guaranteed range is notable given that it is specified as a minimum level for emergencies. This may indicate that respondents either overlooked or misinterpreted this aspect or simply prioritized minimizing risk. Additionally, the experiment included an immediate charge option, allowing users to charge their vehicles at any time. Contrary to expectations and past research (Gschwendtner et al., 2021), this feature appears to have had minimal impact, suggesting it may have been overlooked, misunderstood, or deemed impractical by respondents.

Regarding minimum plug-in time (MP), which was specified for weekdays between 7AM and 7PM, the study reveals mixed results concerning its importance. In contrast to most research, which report a significant negative impact of long plug-in times (Huang et al., 2021; Parsons et al., 2014), this study highlights variability in plug-in time preferences. Two classes (Class 3 and Class 4) place high value on plug-in time, with Class 3 considering it the most important factor. This suggests that, despite most cars being idle for over 95% of the day (Kempton & Letendre, 1997; Parsons et al., 2014), these respondents view the required plug-in time as a potential inconvenience. In contrast, Class 1 and Class 2 place relatively less importance on plug-in time, with it being least important in Class 1. This variability seems linked to regular driving routines and less need for flexibility, such as for non-remote workers and car sharers, who typically have more predictable transportation patterns, hence display less sensitivity to this factor. This finding aligns with research showing that V2G carsharing is more appealing than conventional carsharing (Gschwendtner and Krauss, 2022).

Regarding battery degradation (BD), the results reveal that users in all classes place similar amount of dislike towards battery degradation, with Class 4 assigning it the least relative importance and Class 2 the most, at 8% and 23% respectively. However, in no class is battery degradation the top priority, which contrasts with Huang et al. (2021). This difference may stem from the level of uncertainty that their study included in the attribute, by considering discharging cycles without clarifying its exact effect on battery health. Similarly, Zonneveld (2019) used the same format and found increased demand for V2G as discharging cycles increased, suggesting respondents may have misunderstood the attribute. Overall, although the literature suggests that battery degradation should not be a major issue from a technical perspective (Gschwendtner et al., 2021) and it is not the primary concern for any group, this study still found that a number of respondents showed concern for it.

6.2. Policy implications and general recommendations

The identification of four distinct latent classes representing user preference profiles for adopting V2G yields valuable insights with significant policy implications. This section outlines recommendations for broader V2G adoption based on the study's findings.

First, this study reveals that users are motivated by varying factors, and sheds light on those differences, highlighting the need for tailored incentives and contracts. For instance, the largest group (43% of respondents) prioritizes driving range and shows low sensitivity to financial rewards. For this segment, incentives should focus on reducing range anxiety or emphasizing V2G's environmental and grid benefits. The second-largest group (29%) is less concerned with plug-in times but places a high value on minimizing battery degradation compared to other groups. Offering battery warranties or reducing degradation could be effective strategies to engage this group. The third group (18%) values flexibility, including higher guaranteed range and shorter plug-in times. For them, the focus should be on ensuring vehicle availability and flexibility, possibly by offering lower or customizable plug-in schedules—such as differentiating between weekdays and weekends. Lastly, to attract the smallest group (10%), monetary incentives are the primary motivator.

Second, our findings indicate that individuals who primarily drive EVs or participate in car sharing, place less importance on minimum plug-in times and guaranteed range in their V2G contracts. Since previous research has shown that car sharers are more inclined to drive EVs (Cartenì et al., 2016, Paundra et al., 2017, Schlüter and Weyer, 2019; Mueller et al., 2015), this suggests that greater familiarity with EVs may reduce concerns about flexibility loss associated with V2G. Therefore, providing more opportunities for users to experience EVs firsthand may positively influence their V2G preferences. Furthermore, while this study focuses on individual users, fleet owners (such as car-sharing services or delivery operators) are likely to play a key role in scaling V2G adoption, with aggregators serving as crucial intermediaries between private users and the grid. The user preference insights presented here can help inform how such offerings are designed—an avenue also worth exploring in future research.

Third, the findings suggest that access to charging infrastructure plays a major role in shaping V2G preferences. Users without access to private parking—who could still participate via public or workplace charging—place a high value on flexibility, implying that availability of convenient charging could alleviate range and plug-in concerns. Additionally, frequent commuters and non-remote workers, whose vehicles remain stationary during work hours, are less concerned about plug-in times. This implies that expanding workplace charging and educating users about how often cars are stationary—over 95% of the day on average—and the adequacy of an EV's range for typical usage could further reshape perceptions about plug-in times and range.

Fourth, the results show that addressing general EV concerns has the potential to translate into alleviating V2G concerns. Therefore, initiatives should focus on reducing range anxiety and lowering the initial cost of EV ownership. Alternatively, V2G itself may help ease EV concerns. For example, emphasizing the financial benefits associated with V2G participation—particularly in terms of decreasing the lifetime cost of EV ownership compared to fossil fuel vehicles—could be an effective strategy. Notably, respondents concerned about initial costs of EVs place high value on financial compensation from V2G, supporting Chen et al.'s (2020) suggestion that V2G could serve as a crucial incentive for EV adoption.

Fifth, we find that respondents unfamiliar with V2G tend to prioritize low minimum plug-in times in their preferred V2G contracts. Educational initiatives, such as pilot programs with actual users, can enhance familiarity with V2G and potentially ease concerns around plug-in times. As users become more accustomed to the technology, their reservations about flexibility loss may decrease.

Sixth, continued technical development remains crucial for widespread V2G adoption. As derived from our results, key areas include extending the range of EVs, enhancing charging speeds (as discussed by Huang et al. (2021)), and improving predictive capabilities—for example through Artificial Intelligence (AI) and Machine Learning (ML) algorithms. These improvements would reduce the need for high guaranteed ranges and minimum plug-in times.

Overall, given that guaranteed range is the most critical attribute for most users, we recommend prioritizing solutions to alleviate concerns related to it. These strategies could include offering tailored contracts with higher guaranteed ranges, shifting perceptions to alleviate range anxiety, and pursuing technological advancements such as increasing battery capacity, improving battery management systems, and leveraging predictive AI.

7. Conclusions

This study set out to answer the following research question: *"What are the preferences of potential users towards vehicle-to-grid (V2G) contract elements, and how are these preferences shaped by user-related factors?"*. In order to answer this question, a stated preference survey, containing twelve choice-questions that prompted the respondents to choose between two V2G contracts, was designed and disseminated. Each contract consisted of four contract elements: financial compensation, guaranteed range, minimum plug-in time, and battery degradation—each varied with three levels. The survey also gathered detailed information on user characteristic factors. A total of 1,018 representative participants completed the survey, corresponding to a total of 12,216 observations. The responses were analyzed using a latent class choice model; an advanced statistical approach that accounts for unobserved heterogeneity. The analysis identified four distinct latent classes, each representing different user preference profiles for adopting V2G. Refer to Table 5 for the final model results.

The attribute estimates show that guaranteed driving range receives the highest relative importance in the two largest classes, which together represent 72% of respondents. In the third class (18% of respondents), plug-in time during peak hours (7 AM to 7 PM on weekdays) is weighted most heavily, with guaranteed range receiving the second-highest weight. Financial compensation, while receiving the highest relative importance in the smallest class (10% of respondents), is assigned lower importance in the remaining classes. Battery degradation also ranks consistently low—not receiving the highest relative weight in any class. Notably, in the three larger classes, financial compensation and battery degradation receive similarly low weights and are tied as the lowest-ranked attributes in two of them. The model also offers insights into class membership likelihoods based on a range of user characteristics, including socio-demographic (e.g., gender, age, income), household (e.g., household composition, children, living area), car use (e.g., car type, driving frequency), and attitude and preference factors (e.g., environmental consciousness).

While this study provides valuable insights into V2G user preferences, several limitations should be noted. First, the stated preference approach relies on hypothetical scenarios, which may not fully reflect real-world decision-making. This is particularly relevant for V2G, as the technology is still in its early stages, meaning most respondents have little to no practical experience with it. Second, to maintain clarity and focus, the survey concentrated on a limited set of contract elements, potentially overlooking other important factors, such as upfront costs, contract flexibility, or broader incentives like environmental benefits. Third, although the sample is representative, it may not capture the full diversity of V2G users across different regions or driving cultures. Future research could address these limitations by conducting longitudinal studies to track evolving preferences, broadening the scope of contract elements, and investigating V2G adoption in specific regions or among niche groups, such as early adopters. Practical recommendations include providing tailored incentives and flexible contracts to meet diverse user preferences, while addressing concerns such as range anxiety and battery degradation through education, technological advancements, and improved charging infrastructure.

Finally, this research highlights the complexity and nuance of user preferences related to the V2G innovation. By applying a latent class model and incorporating a wide range of user characteristics, the study provides valuable insight into preference heterogeneity across segments. Drawing on a large and diverse sample (>1,000 respondents)—including both EV and non-EV drivers, as well as various car ownership types such as car sharing—it reveals key differences between potential user groups and identifies numerous user-related factors linked to class membership. These findings contribute to a more comprehensive understanding of the complex factors shaping V2G preferences and significantly enrich the existing knowledge base.

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CRediT authorship contribution statement

Jerico Bakhuis: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Natalia Barbour:** Writing – review & editing, Validation, Supervision, Methodology, Data curation, Conceptualization. **Eric Molin:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Émile J.L. Chappin:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization.

Appendix A: Sample composition

Table A1 shows the descriptive statistics of statistically significant variables in the final model. Starting with the socio-demographic characteristics, we find a consistent age distribution across each ten-year interval, with the highest share (24%) aged above 65 years. Gender identification shows a balanced distribution between male (53%) and female (47%) respondents. Education levels vary, with similar distributions across VMBO high-school level[12] (20%), Secondary vocational education (23%), Bachelor of applied science (28%), and Masters' degree or higher (20%) qualifications. Income distribution is varied, with a large fraction earning between €20,001 and €60,000 (55%), with about equal distributions with every €10,000 increase between that range of on average 14%. Work situations differ, with a majority in full-time (23%) or part-time (18%) employment and 23% not currently in the labor market.

Regarding household characteristics, the respondents have diverse household sizes, with a significant portion (45%) comprising two-person households. Household composition varies, with a substantial number (42%) living with a partner without children and a corresponding majority of two-person households (45%). The majority (70%) of respondents do not have children in their household. Regarding living area, the distribution is relatively equally distributed between urban (38%, suburban (32%) and rural (29%), and the majority (60%) have home parking access. Furthermore, home renewable energy use stands at 48%.

Regarding car use characteristics, we find that respondents predominantly drive fossil-based cars (71%), followed by hybrid electric cars (18%) and battery electric cars (11%). Regarding car access type, car ownership is widespread (88%), and private leasing and car sharing, while less common (11% each) are still well-represented in the data. A noteworthy 55% of individuals report never engaging in remote work, while 28% work remotely 2 days per week or less. Commute length varies, with 29% having no commute, and 28% having commutes lasting 15 to 30 min. Regarding driving frequency, the majority drive a minimum of 1 day per week (86%), with 38% driving 5 days or more per week. The car use indicators show how for what purpose individuals drive their cars, with varied distributions for commuting, errands and leisure activities. Furthermore, a majority drives their car for more than 50 km for more than 1 or 2 times per month (93%).

Finally, regarding attitude-related variables, we observe a range of diverse attitudes. Regarding familiarity with V2G, a significant portion of respondents (63%) had never heard of it, while 19% had heard of it but were not very familiar. In terms of the likelihood of participating in a V2G program, the majority of respondents express positive sentiments, with 31% stating they are likely and 11% indicating they are very likely to participate. When assessing the importance of a car in terms of freedom and mobility, a substantial portion deem it fairly important (40%) or very important (43%), covering 83% of all respondents. Similarly, attitudes towards environmental sustainability in overall decision-making reveal that 43% consider it fairly important and 18% consider it very important. Regarding attitudes toward the use of new technologies, the majority are fairly enthusiastic (46%) and very enthusiastic (16%), reflecting a positive stance. Notably, concerns about EVs are evident, with 58% expressing concerns about driving range and 51 % about initial costs.

[12] The Dutch educational system has separate high-school levels, with VMBO/MAVO being a lower level and HAVO/VWO being the highest levels.

Table A1
Descriptive statistics for user characteristic variables.

User Characteristics	Variable	Categories	Percentage (%)
Socio-demographic factors	**Gender Identification***	Male	53%
		Female	47%
		Other	0%
	Age*	18 – 24	4%
		25 – 30	9%
		31 – 40	17%
		41 – 50	17%
		51 – 60	19%
		61 – 65	10%
		> 65	24%
	Education*	Primary school	1%
		VMBO or MAVO**	15%
		HAVO or VWO	7%
		Secondary vocational education (MBO)	23%
		Bachelor of applied science (HBO)	28%
		Bachelor of science	6%
		Master of science or higher	20%
	Income	Less than € 20.000	7%
		€20.000 – €30.000	12%
		€30.001 – €40.000	16%
		€40.001 – €50.000	15%
		€50.001 – €60.000	12%
		€60.001 – €70.000	9%
		€70.001 – €80.000	8%
		€80.001 – €90.000	6%
		€90.001 – €100.000	4%
		More than €100.000	11%
	Work situation	Full-time (more than 32 hours per week)	43%
		Part-time (up to 32 hours per week)	18%
		Self-employed or Freelancer	6%
		Not on the labor market	23%
		Student	2%
		Retired	9%
		Stays at home	1%
Household factors	**Household size**	One person	18%
		Two persons	45%
		Three persons	16%
		Four persons	17%
		Five or more persons	4%
	Household composition	Single	21%
		Living with a partner without children	42%
		Living with a partner and children	31%
		Single parent with children	5%
		Living with parents	1%
		Living together with housemates	1%
	Children in the household	No children	70%
		One child	12%
		Two children	14%
		Three children	4%
		Four or more children	0%
	Living area	Urban	38%
		Suburban	32%
		Rural	29%
		Village	1%
	Home parking Access	Yes	60%
		No	40%
	Home renewable energy use	Yes	48%
		No	52%
	Electricity bill	Less than €50	21%
		€51 – €100	32%
		€101 – €150	23%
		€151 – €200	11%
		€201 – €250	6%
		€251 – €300	3%

(continued on next page)

Table A1 (*continued*)

User Characteristics	Variable	Categories	Percentage (%)
		€301 – €350	1%
		€351 – €400	1%
		More than €400	1%
Car use factors	**Car type***	Full Electric	11%
		Hybrid Electric	18%
		Fossil Fuel	71%
	Car access type — ownership	Yes	88%
		No	12%
	Car access type — private lease	Yes	11%
		No	89%
	Car access type – car sharing	Yes	11%
		No	89%
	Remote working frequency	Never	55%
		Less than 1 day per week	8%
		1—2 days per week	20%
		3—4 days per week	14%
		5 or more days per week	3%
	Commute length	I do not have a daily commute	29%
		Less than 15 min	12%
		15 to 30 min	28%
		31 to 60 min	21%
	Driving frequency	Less than 1 day per year	1%
		1—5 days per year	4%
		6—11 days per year	2%
		1—3 days per month	7%
		1—2 days a week	25%
		3—4 days a week	24%
		5—6 days a week	18%
		(Almost) every day	20%
	Car use type – daily commute	0 day	32%
		1 day	12%
		2 days	8%
		3 days	10%
		4 days	11%
		5 days	16%
		6 days	6%
		7 days	6%
	Car use type – errands	0 day	12%
		1 day	25%
		2 days	23%
		3 days	15%
		4 days	9%
		5 days	8%
		6 days	4%
		7 days	4%
	Car use type – leisure activities	0 day	3%
		1 day	30%
		2 days	26%
		3 days	15%
		4 days	10%
		5 days	8%
		6 days	4%
		7 days	5%
	Long journey (>50 km) frequency	Never	7%
		1—2 times a month	45%
		3—5 times a month	24%
		6—10 times a month	12%
		11—20 times a month	8%
		More than 20 times a month	5%
Attitude factors	**V2G familiarity**	Never heard of it before	63%
		Heard of it, but not so familiar	19%
		Somewhat familiar	11%
		Fairly familiar	3%
		Very familiar	4%
	Likelihood of participating in a V2G program if it were available	Very unlikely	12%
		Unlikely	14%
		Neutral	32%
		Likely	31%

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Table A1 (*continued*)

User Characteristics	Variable	Categories	Percentage (%)
		Very likely	11%
	Importance of car in terms of freedom and mobility	Not important at all	1%
		Not so important	4%
		Neutral	12%
		Fairly important	40%
		Very important	43%
	Importance of environmental sustainability in overall decision-making	Not important at all	5%
		Not so important	9%
		Neutral	24%
		Fairly important	43%
		Very important	18%
	Attitude towards the use of new technologies	Very reserved	3%
		Hesitant	10%
		Neutral	25%
		Fairly enthusiastic	46%
		Very enthusiastic	16%
	EV concerns – driving range	Yes	58%
		No	42%
	EV concerns – initial costs	Yes	51%
		No	49%

* Indicate the quota statistics that were monitored during data collection for representativeness and a varied response.
** VMBO and MAVO are lower levels of secondary education; HAVO and VWO are higher levels.

Appendix B: Latent class model equations

In our experiment, participants chose between two unlabeled contracts (A and B), each defined by four attributes. Let y_{it} represent the choice made by participant i in choice task t. Since the experiment is unlabeled, only generic effects are estimated—meaning no alternative-specific constants or alternative-specific attribute effects are included. The stated choices y_{it} are indicators of the latent systematic utility, denoted as $\eta_{m|z_{it}}$, which represents the utility of each alternative m (either V2G contract A or B) in choice task t for respondent i. The latent utility is modeled as:

$$\eta_{m|\boldsymbol{z}_{itm}} = \sum_{k=1}^{K} \beta_k z_{itkm}^{att} + \varepsilon_{itm} \tag{1}$$

In which β_k represents the effect of attribute k and z_{itkm}^{att} represents the value of attribute k for alternative m in choice task t for respondent i. The ε_{itm} represents the disturbance term.

Since latent class models assume that the sample population belongs to X different latent classes, each with distinct taste parameters, the utility function of members from class x is given by:

$$\eta_{m|x,\boldsymbol{z}_{itm}} = \sum_{k=1}^{K} \beta_{xk} z_{itkm}^{att} + \varepsilon_{itm} \tag{2}$$

This equation implies that a different set of β_{xk} will be estimated for each class x. The disturbance term ε_{itm} is assumed to be extreme-value distributed (McFadden, 1981), giving rise to the MNL form. Thus, the conditional probability of respondent i choosing alternative m in task t, given their class x, follows the MNL function (see Greene and Hensher, 2003):

$$P(y_{it} = m|x, \boldsymbol{z}_{it}) = \frac{\exp(\eta_{m|x,\boldsymbol{z}_{it}})}{\sum_{m'=1}^{M} \exp(\eta_{m'|x,\boldsymbol{z}_{itm'}})} \tag{3}$$

For each subject i, the probability of belonging to a class x is determined by their individual characteristics $\boldsymbol{z}_i^{cov}$ which are termed "covariates". This probability function also takes the form of an MNL model:

$$P(x|\boldsymbol{z}_i^{cov}) = \frac{\exp(\gamma_{x0} + \sum_{r=1}^{R} \gamma_{xr} z_{ir}^{cov})}{\sum_{x'=1}^{X} \exp(\gamma_{x'0} + \sum_{r=1}^{R} \gamma_{x'r} z_{ir}^{cov})} \tag{4}$$

In this class membership model, an intercept (γ_{x0}) and a set of regression coefficients (γ_{xr}) are estimated for each class. These covariates (r) represent user characteristics such as socio-demographic factors and serve as indicator variables to help explain class membership.

Finally, the probability of observing a certain sequence of choices y_i for respondent i is given by:

$$P(\boldsymbol{y}_i) = \sum_{x=1}^{S} P(x|\boldsymbol{z}_i^{cov}) \prod_{t=1}^{T} P(y_{it} = m|x, \boldsymbol{z}_{it}) \tag{5}$$

Latent class models can be readily estimated using maximum likelihood procedures (refer to Greene and Hensher (2003) and Shen (2014) for a detailed explanation of the model structure and estimation process).

Appendix C: Survey explanations

This appendix contains the explanatory text presented to respondents to introduce the concept of V2G and clarify the survey design. Please note that the original survey was conducted in Dutch; the content below is an English translation.

Survey introduction

Thank you for participating in this survey on the interest of car drivers in vehicle-to-grid (V2G). More information about V2G will follow. The survey is open to all persons over 18 years old with a valid driver's license in the Netherlands. Our goal is to gain better insight into the willingness of car drivers to participate in V2G, the factors that influence this decision and how the technology and services of V2G programs can be improved. This survey will take approximately 10 minutes.

For this survey you will remain completely anonymous and your data will be treated confidentially. If you have any questions or comments, you can contact me at [insert email].

What is V2G

Vehicle-to-grid (V2G) is an innovation that allows electric vehicles to not only charge, but also discharge. When connected to a charging point, vehicles can store excess electricity, for example from solar energy, and deliver it back to the electricity grid when needed. Because of this discharge capability, V2G can play an important role in the energy transition to stabilize our energy system and promote the reduction of environmental pollution.

In a **V2G program**, participants are offered financial compensation if they allow a third party (such as an energy company) to not only charge but also discharge the battery of their vehicle.

This survey in a nutshell

Imagine you own an electric vehicle and a third party offers you a contract to participate in a vehicle-to-grid (V2G) program. We would like to know what your preference would be if multiple V2G contracts were possible.

- After this page, you will be presented with several such V2G contracts, each consisting of four elements (see image below).
- For each set of contracts, select your preferred contract option, based on the different values of the four elements.

Contract Elements	Contract Options	
	V2G Contract A	V2G Contract B
Financial Compensation	€40,- *per month*	€140,- *per month*
Guaranteed Range	75 *km*	75 *km*
Minimum Plug-in Time Working days between 7am and 7pm	2 *hours per day*	8 *hours per day*
Extra Battery Degradation	2% *per year*	1% *per year*

Explanation of the V2G contracts

The four **contract elements** are:

- **Financial Compensation:** A guaranteed fixed payment is deposited into your bank account every month;
- **Guaranteed Range:** Your vehicle always maintains a minimum battery level, so that you can cover essential distances, such as an emergency trip to the hospital;
- **Minimum Plug-in Time:** The contract specifies a minimum period during which your vehicle must be connected to a charging point during peak hours (weekdays between 07:00 and 19:00). As long as you meet the monthly average, you can use your car at any time. If not, no compensation is provided for that month;
- **Additional Battery Degradation:** V2G can accelerate battery degradation beyond the typical annual decline of 1–2%, while a battery is typically replaced when it reaches 70–80% of its original capacity. Although the exact amount is uncertain, the contract specifies the estimated maximum additional degradation.

Each contract has the following **basic components**:

- By default, your car switches to V2G when it is connected to a charging point. You can opt out of V2G at any time via an **app** and only charge your car.
- The same **app** shows the number of hours your car has been connected during peak hours. If you do not meet the monthly average required plug-in time, no compensation will be provided for that month.

Appendix D: Contract acceptance

This appendix presents additional analyses of contract acceptance, based on the follow-up *yes/no* question posed after each choice task. Acceptance rates are shown both overall and by latent class, across the twelve choice tasks. These visualizations allow for a more granular interpretation of how respondents' willingness to accept contracts varies by class and task. To aid interpretation, the attribute levels used in each task are presented here shown in Table D1 below.

Table D1
Contract attribute levels per choice task.

Choice task	Contract	Financial Compensation (FC) *(€/month)*	Guaranteed Range (GR) *(km)*	Minimum Plug-in Time (MP) *(hour per day during peak hours)*	Battery Degradation (BD) *(annual additional %)*
1	A	40	75	2	2
	B	140	75	8	1
2	A	140	75	2	2
	B	90	125	8	2
3	A	40	125	5	3
	B	140	25	5	3
4	A	90	125	8	2
	B	140	125	5	3
5	A	140	125	5	3
	B	140	75	2	2
6	A	140	25	5	3
	B	40	75	2	2
7	A	140	75	8	1
	B	90	125	2	1
8	A	90	125	2	1
	B	140	25	5	2
9	A	40	75	8	1
	B	90	25	2	1
10	A	90	25	2	1
	B	40	125	5	3
11	A	40	125	5	3
	B	90	25	8	2
12	A	90	25	8	2
	B	40	75	8	1

Overall acceptance rate per task

Across the full sample, acceptance rates remain relatively stable across the twelve tasks, ranging between approximately 43% and 62%, with an average of 53%. This suggests that, despite varying attribute combinations, most choice tasks elicited a similar level of contract acceptance (see Figure D1).

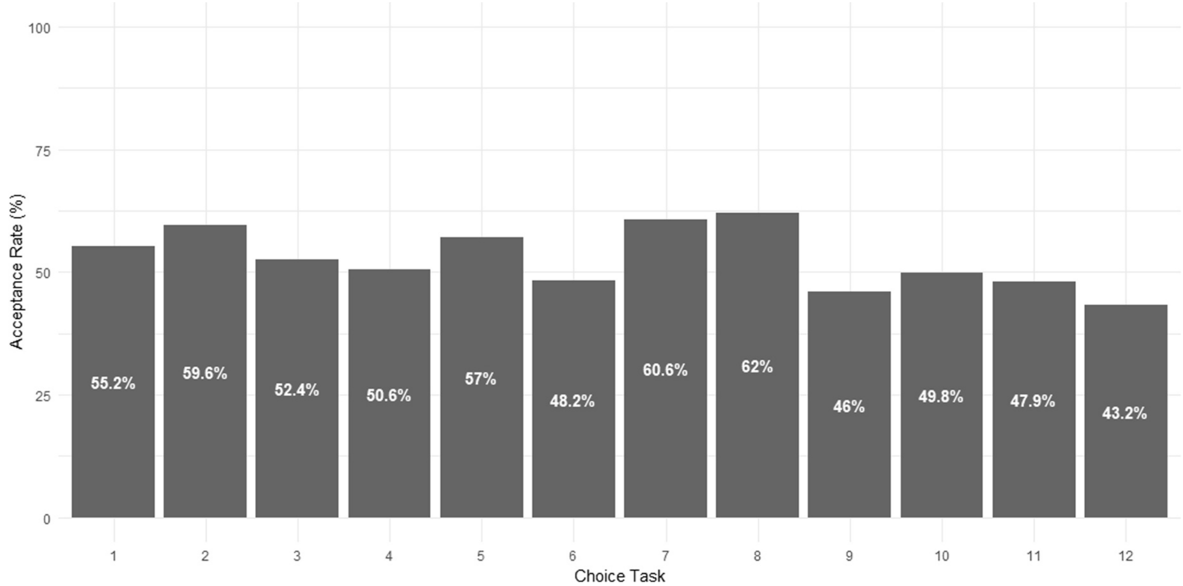

Fig. D1. Acceptance by choice task (n = 1,018); mean = 53%.

Acceptance per task by class

Breaking down acceptance by class also reveals generally consistent patterns across tasks for most groups (see Figures D2–D5), with average acceptance rates for Classes 1–4 of 48%, 60%, 46%, and 64%, respectively. Classes 1, 2, and 4 exhibit relatively stable acceptance levels with limited variation (see Figures D2, D3 and D5). In contrast, Class 3 shows more pronounced fluctuations across tasks (Figure D4). This group reports notably high acceptance in Tasks 2 and 7, but substantially lower rates in Tasks 11 and 12. These latter tasks feature contracts with less favorable guaranteed range and plug-in time (see Table D1)—two attributes that are particularly important to this flexibility-oriented segment.

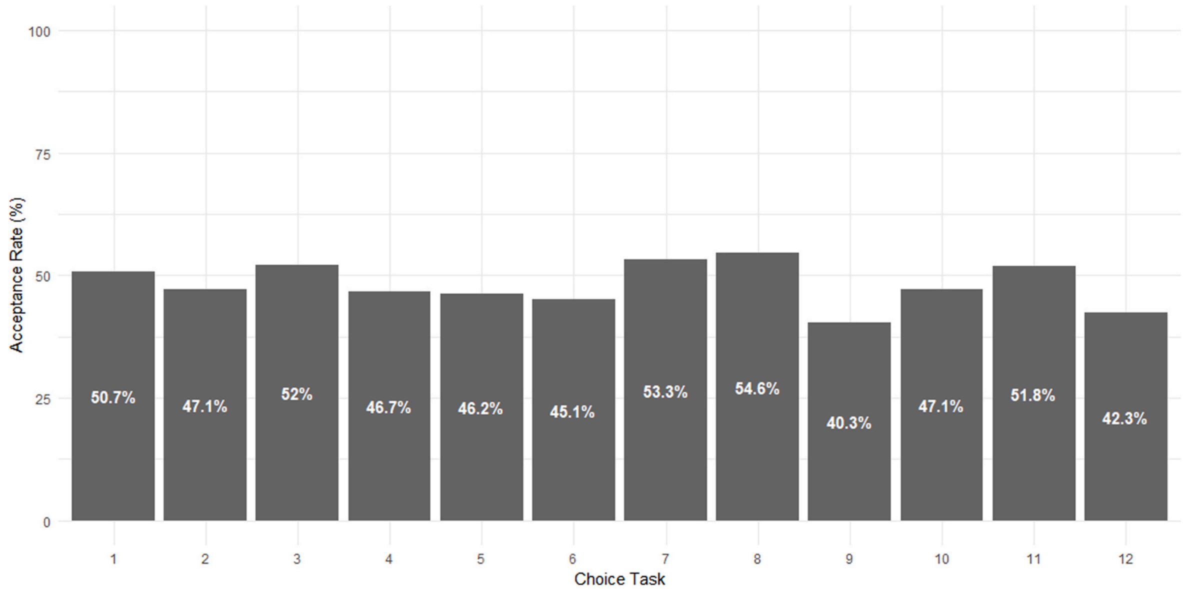

Fig. D2. Class 1 acceptance by choice task (n ≈ 452); mean = 48%.

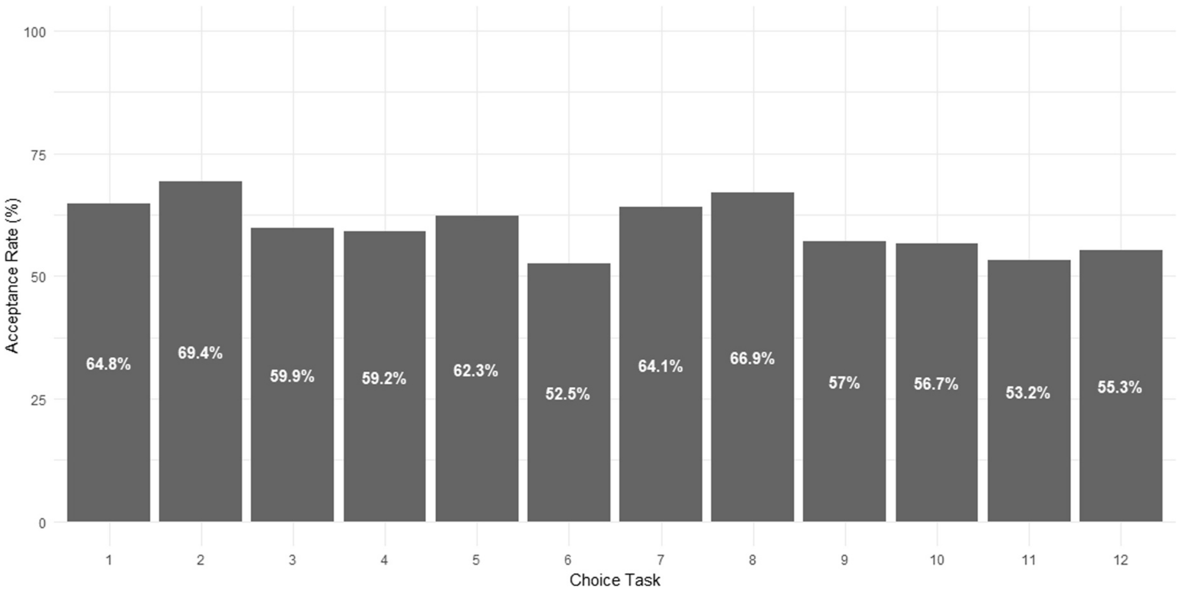

Fig. D3. Class 2 acceptance by choice task (n ≈ 284); mean = 60%.

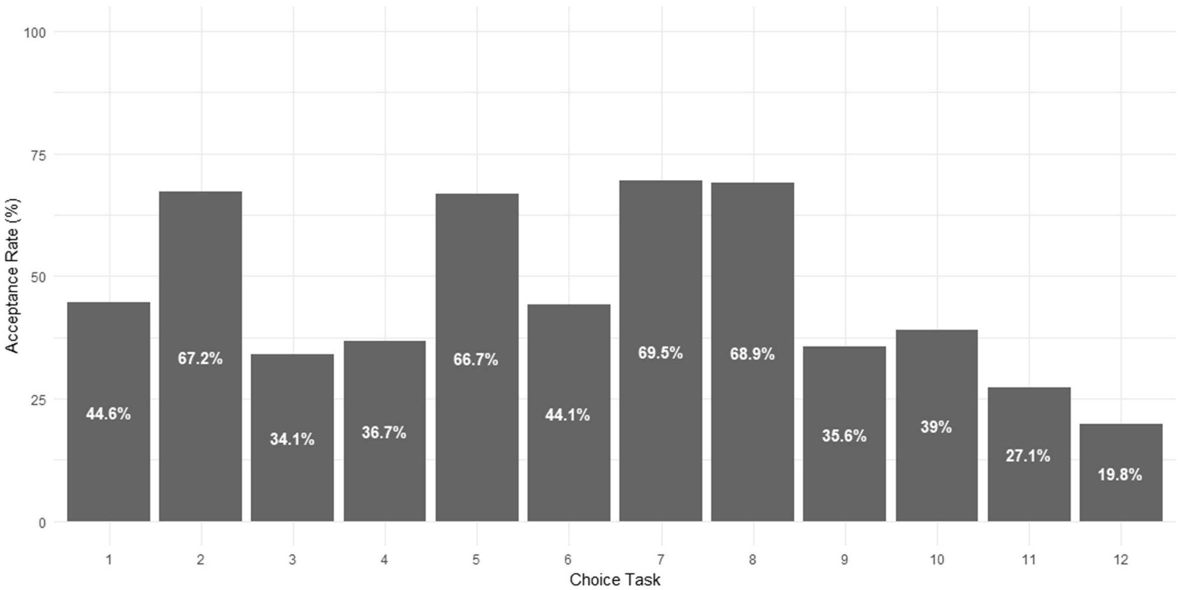

Fig. D4. Class 3 acceptance by choice task (n ≈ 177); mean = 46%.

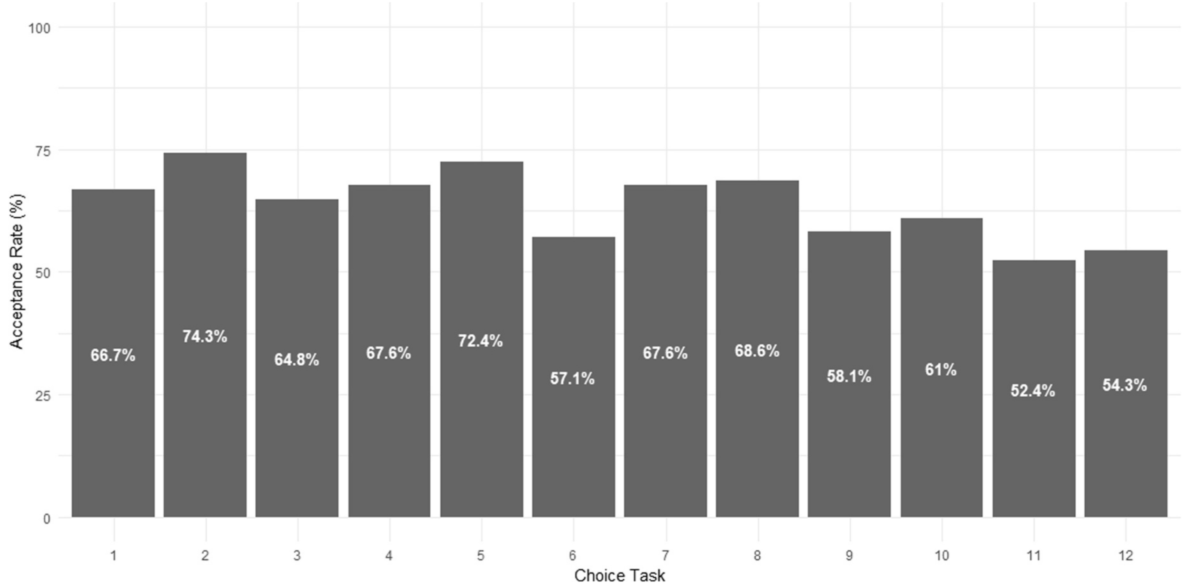

Fig. D5. Class 4 acceptance by choice task (n ≈ 105); mean = 64%.

Acceptance by chosen contract

When acceptance is broken down by the chosen contract (A or B), task-level differences become more pronounced (see Figure D6)[13]. In Task 2, for example, contract A is not only chosen more often (601 vs. 417), but also accepted significantly more frequently. These patterns indicate that contract-specific characteristics—not just class-level preferences—can strongly influence acceptance.

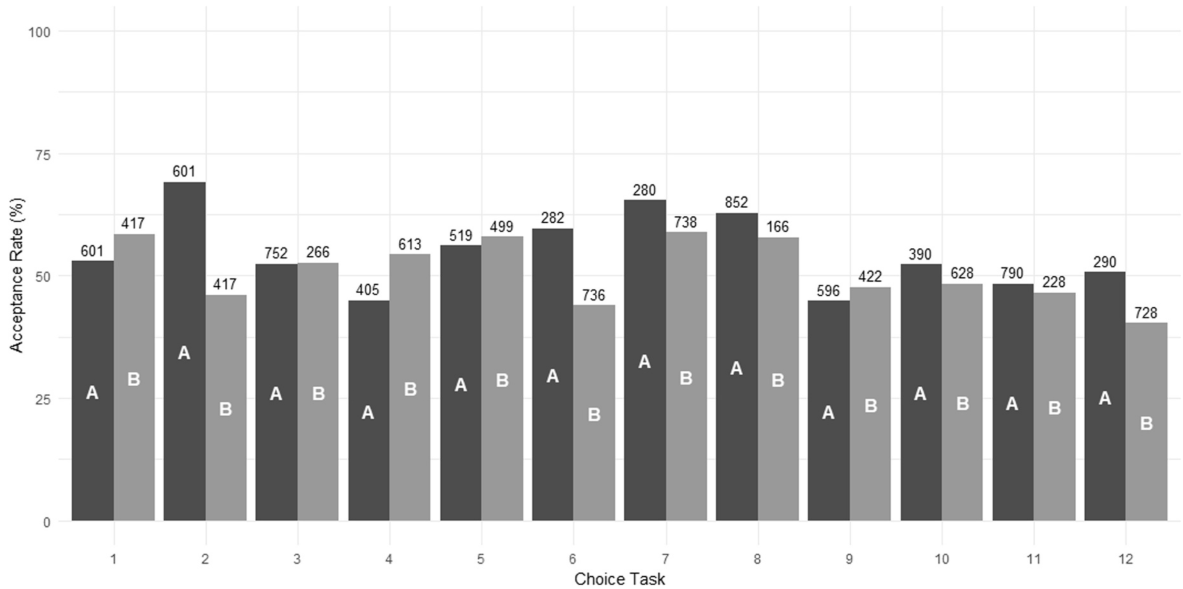

Fig. D6. Acceptance by chosen contract (n = 1,018).

[13] In Figures D6–D10, the numbers above each bar indicate how many respondents in the respective class chose the corresponding contract. The height of each bar reflects the percentage of those respondents who accepted the contract.

Acceptance by chosen contract by class

Analyzing acceptance by both class and chosen contract provides more nuanced insights (see Figures D7–D10). For instance, Class 3 shows strong acceptance patterns in Task 7 and Task 9 (Figure D9), where contracts better align with their preference for flexibility. Meanwhile, in Task 2, Class 4 members unanimously chose and widely accepted contract A (Figure D10). This contract offered the highest financial compensation and shortest plug-in time—attributes most valued by this financially motivated group (see Table D1).

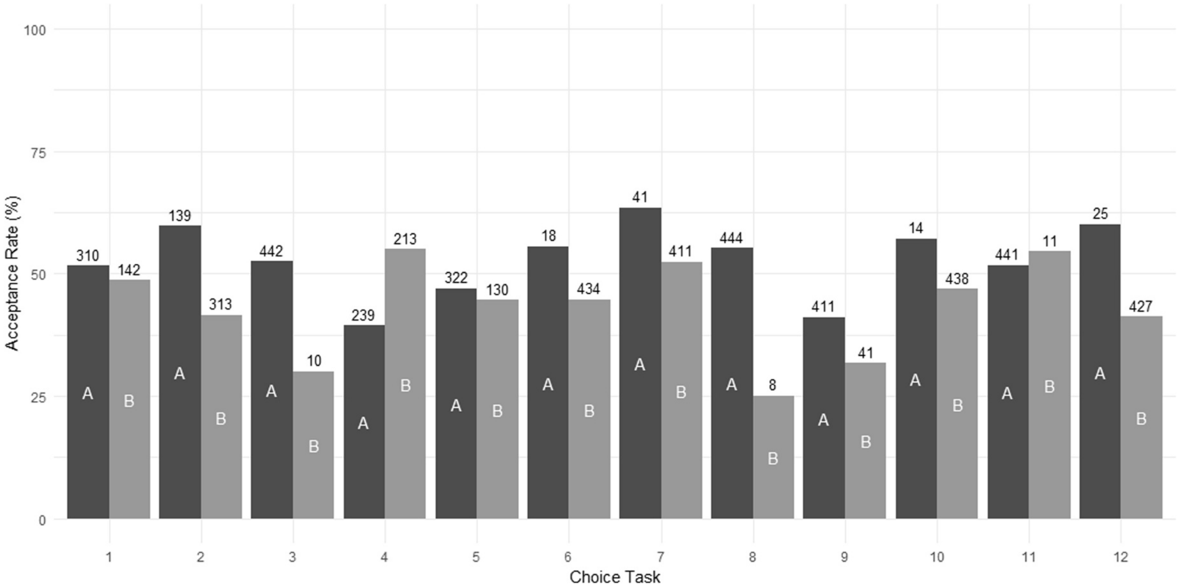

Fig. D7. Class 1 acceptance by chosen contract (n ≈ 452).

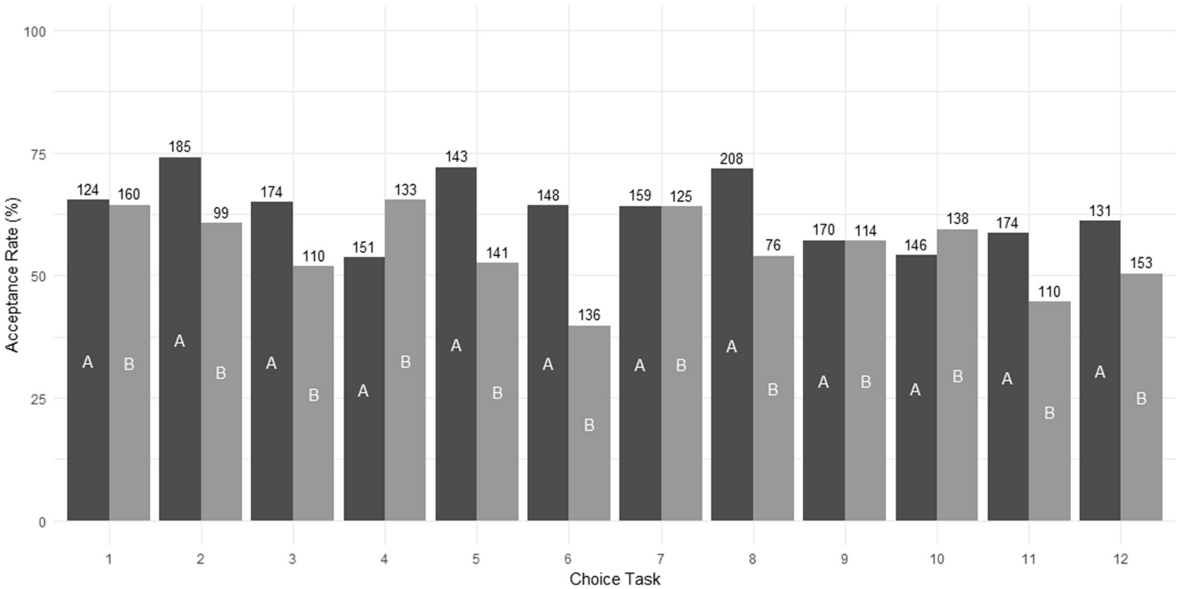

Fig. D8. Class 2 acceptance by chosen contract (n ≈ 325).

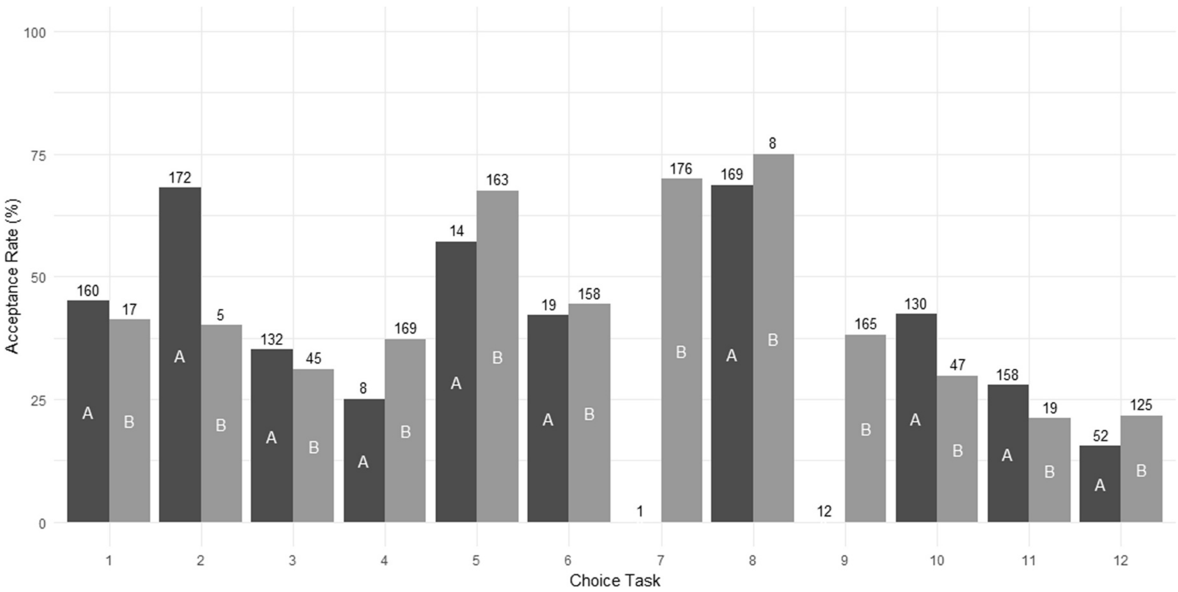

Fig. D9. Class 3 acceptance by chosen contract (n ≈ 136).

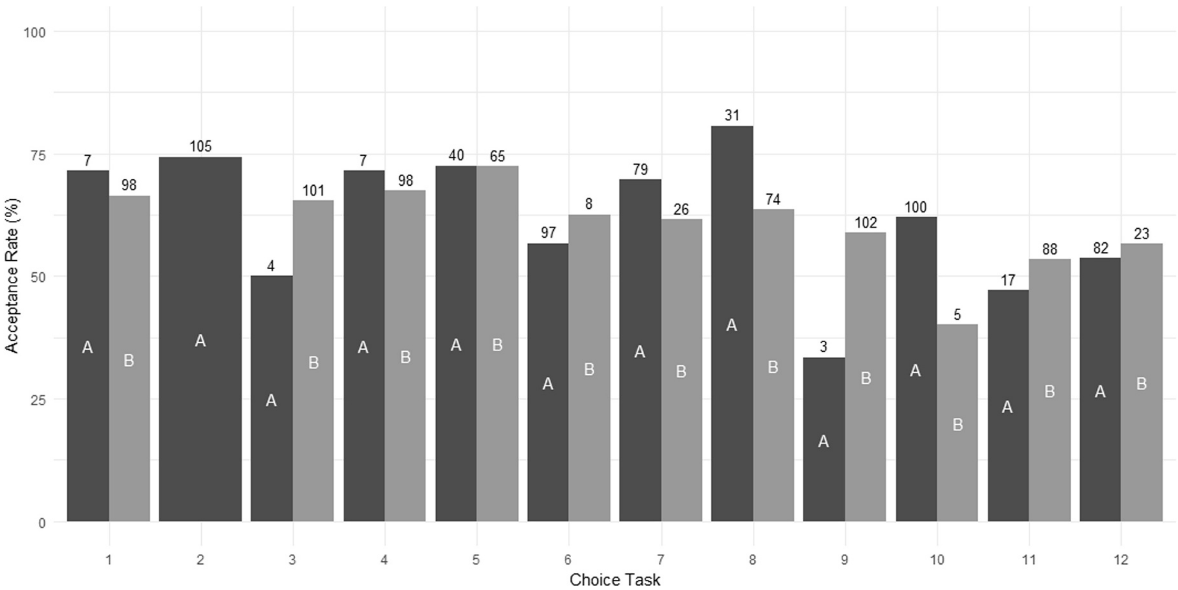

Fig. D10. Class 4 acceptance by chosen contract (n ≈ 105).

These patterns reinforce earlier findings from the latent class model and provide insight into how acceptance is influenced not just by attribute preferences, but also by the match between contract structure and user segment.

Appendix E: Willingness to pay (WTP) estimates

To provide practical insights into user trade-offs, we calculated the willingness to pay (WTP) for each contract attribute across the latent classes. WTP represents the monetary value that respondents assign to changes in non-monetary attributes—specifically, guaranteed range, minimum plug-in time, and battery degradation—based on their marginal rate of substitution with financial compensation (€/month). It is calculated as:

$$WTP_x = \frac{\beta_x}{\beta_{FCx}}$$

Where β_x is the estimated coefficient of the attribute, and β_{FCx} is the financial compensation coefficient in the same class x. Positive WTP values represent how much respondents are willing to forgo in monthly compensation to gain an improvement in an attribute;

negative values indicate the required additional compensation to accept a deterioration. For example, a WTP of –€82.86 per hour of additional plug-in time (Class 3) means users would require €82.86 more per month to accept this change. The WTP estimates are shown in Table E1.

Table E1
Estimated willingness to pay (€/month) for attribute changes by class.

Class	Guaranteed Range (€ per km added)	Minimum Plug-in Time (€ per additional hour/day)	Battery Degradation (€ per 1% increase)
Class 1*	–	–	–
Class 2	€2.50	−€5.00	−€45.00
Class 3	€2.86	−€82.86	−€51.43
Class 4	€0.03	−€4.86	−€5.95

* Class 1 exhibits a negative coefficient for financial compensation, reflecting a non-linear utility pattern and lower prioritization of monetary incentives (see Section 5.2.1 for further discussion). As a result, standard WTP interpretation does not apply, and we do not report WTP values for this group.

These WTP estimates offer a monetary lens through which to interpret user preferences and help clarify the trade-offs individuals are willing to make. They reflect the same underlying insights as the relative importance values presented in Table 5—for instance, classes that place high importance on plug-in time also require substantial compensation to accept longer plug-in durations. Overall, the estimates suggest that for many users, non-monetary attributes are more influential than direct financial incentives in shaping preferences for V2G contracts.

That said, given the early-stage nature of V2G and the lack of commercial implementation, we caution against using these values for direct quantitative policy design.

Appendix F: Summary of findings

This appendix summarizes the four latent class profiles identified in the analysis. Table F1 presents the ranked attribute importance for each latent class based on relative importance (RI%) values for financial compensation, guaranteed range, minimum plug-in time, and battery degradation. For full model estimates, see Table 5 in Section 5.

Table F1
Summarized latent class profiles. Attribute importance is ranked based on relative importance (RI%) values for Financial Compensation (FC), Guaranteed Range (GR), Minimum Plug-in Time (MP), and Battery Degradation (BD). Refer to Table 5 in Section 5 for detailed model estimates.

Class	% of sample	Ranked attribute importance (RI %)	Class membership
***Class 1:** Range-Focused and Finance-Disregarding Users*	43%	1. GR (66%) 2. BD (13%) 3. MP (12%) 4. FC (9%)	**More likely** • Female • Older age (65+) • Employed • Drive fossil fuel vehicles • Commute frequently (5+ days/week) • Use renewables at home **Less likely** • Very likely to adopt V2G if available
***Class 2:** Range-Focused and Plug-in Time-Disregarding Users*	29%	1. GR (45%) 2. FC (23%) 3. BD (23%) 4. MP (9%)	**More likely** • Male • Younger age (18–24) • Lower income (€60,000 or less) • High school diploma or higher • Live with partner (no children) • Rural residents • Car owners, private leasers, and/or sharers • Frequent leisure car use (5+ days/week) **Less likely** • Never work remotely

(continued on next page)

Table F1 (*continued*)

Class	% of sample	Ranked attribute importance (RI %)	Class membership
			• Unfamiliar with V2G
Class 3: *Flexibility-Focused Users*	18%	1. MP (53%) 2. GR (25%) 3. FC (11%) 4. BD (11%)	**More likely** • Higher educated (Master's or higher) • Higher income (€60,000 or higher) • No private parking access • Drive frequently (5+ days per week for errands) • Occasionally take long trips (>2 times per month) • Unfamiliar with V2G • Concerned about EV range **Less likely** • Larger households (4+ people) • Living with partner and children • Car owners • Car-sharing participants • Value environmental sustainability • Concerned about EV costs
Class 4: *Finance-Focused and Range-Disregarding Users*	10%	1. FC (70%) 2. MP (20%) 3. BD (8%) 4. GR (2%)	**More likely** • Households with 3+ children • Private parking access • Unfamiliar with V2G • Likely to participate in V2G • Reserved attitude toward new technologies • Concerned about EV costs **Less likely** • Frequent errand drivers (5+ days/week) • Strong car attachment • Concerned about EV range • Use renewables at home

Data availability

Data will be made available on request.

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