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Exploring user willingness to adopt vehicle-to-grid (V2G): A statistical analysis of stated intentions

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A B S T R A C T

The vehicle-to-grid (V2G) innovation—which enables electric vehicles to return stored electricity to the grid—holds significant potential to support renewable energy integration and electric vehicle adoption. Despite growing interest in V2G, there is still limited understanding of user preferences and the factors influencing decision-making. To explore this, we conducted a stated intention study with 1018 participants, examining their likelihood of participating, and their primary drivers and barriers. Our analysis—using a random parameters order probit model and mixed logit models—revealed that most respondents were likely to participate (42%) or remained neutral (32%). Financial incentives were the primary driver (49%), followed by electricity grid-stability (26%) and environmental (25%) factors. The main barrier for most was loss of flexibility (55%), followed by battery degradation (27%) and data concerns (18%). The study highlights how user characteristics—including socio-demographic, household, car use, and attitude factors—influence these preferences. Finally, we provide policy recommendations, including targeted education and communication, income-based incentives, accessible charging infrastructure, and a regulatory framework supportive to technology development and user protections.

1. Introduction

The vehicle-to-grid (V2G) innovation has garnered increasing attention from both academia and industry due to its potential to transform electric vehicle (EV) batteries into mobile energy storage units that can support the electricity grid (Kempton and Letendre, 1997; Kempton and Tomić, 2005). In essence, V2G enables EVs to not only adjust their charging rates (uni-directional flow)—known as smart charging—but also to discharge stored electricity back into the grid (bi-directional flow) (Kempton and Tomić, 2005; Mwasilu et al., 2014; Robledo et al., 2018). This capability offers several potential benefits, including improved integration of intermittent renewable energy, enhanced grid efficiency, and economic advantages for EV owners (Noel et al., 2017; Lund and Kempton, 2008; Niesten and Alkemade, 2016). By bridging the electricity and transport sectors, V2G has the potential to contribute significantly to decarbonization across both sectors.

Despite these advantages and the growing number of (commercial) pilot projects (NUVVE, 2017; V2G Hub, 2025), V2G remains in its early stages, facing numerous barriers to widespread commercialization. Currently, 151 pilot projects are underway across 27 countries—primarily proof-of-concept trials (52%) or small-scale commercial trials (20.3%)—while only a fraction (9.8%) have reached commercial deployment (V2G Hub, 2025). Europe leads in V2G developments, hosting 99 of these projects, with the Netherlands emerging as a front-runner, operating 20 pilots.

Both pilot programs and academic research have identified a range of barriers spanning technical, institutional, and social dimensions (Sovacool et al., 2017; Gschwendtner et al., 2021; Bakhuis et al., 2025a; Noel et al., 2019b). While early research primarily focused on technical aspects, more recent findings indicate that non-technical factors—particularly consumer acceptance—now represent the most significant hurdles (Kempton and Tomić, 2005; Zecchino et al., 2019; Bakhuis et al., 2025a). Since V2G requires vehicles to remain connected to the grid while parked and owners to consent to bi-directional charging, consumer[1] willingness is crucial. Although vehicles are typically parked 95% of the time (Kempton and Letendre, 1997; Parsons et al., 2014), various concerns—such as battery degradation and reduced state of charge—continue to hinder adoption. Overcoming

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[1] When participating in V2G, consumers can also be referred to as prosumers—individuals who both consume and produce electricity.

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these concerns requires appropriate incentives, such as financial benefits or a greater emphasis on environmental advantages (Li et al., 2015).

While consumer acceptance has been relatively understudied, a growing body of research has begun to explore consumer preferences, particularly through choice experiments (Parsons et al., 2014; Geske and Schumann, 2018; Kubli et al., 2018; Zonneveld, 2019; Huang et al., 2021; Noel et al., 2019c; Kajanova et al., 2021) and qualitative interview-based studies (Kester et al., 2018; Noel et al., 2019a; Sovacool et al., 2019; van Heuveln et al., 2021). These studies offer valuable insights into what potential users prioritize in V2G contracts, their willingness to pay for V2G-enabled EVs, and their perceptions of its benefits and risks. However, important gaps remain, particularly in understanding the likelihood of user participation, the primary determinants—both motivational drivers and perceived barriers—influencing this decision, and how preferences are shaped by individual user characteristics, such as socio-demographics and attitudes.

To address these gaps and expand our understanding of consumer acceptance, this study explores the following research question: *"What is the likelihood of potential users to participate in a V2G program, and how important are various drivers and barriers for their willingness to participate?"* The second part of this question aims to provide a policy outlook into how to promote future participation. Central to our analysis is the relationship between potential users' characteristics and their preferences—a critical factor in understanding and supporting V2G adoption.

To answer this question, we conducted a stated preference survey in the Netherlands. Eligible participants were individuals with a valid driver's license, residing in the Netherlands, and having regular access to a car. The final sample consists of 1018 respondents, representing a diverse group of both EV and non-EV drivers, including car owners, leasers, renters and car-sharers.

For data analysis, we applied two different statistical modeling approaches. To assess the likelihood of participation, we used a random parameters ordered probit model. To examine the drivers and barriers, we estimated two separate mixed logit models. Both modeling techniques account for unobserved heterogeneity in the data, providing a more nuanced understanding of the factors influencing consumer decisions.

The paper is organized as follows. Section 2 presents the literature review. Section 3 details the survey design and data collection procedures. Section 4 outlines the analytical methods and model estimation. Section 5 presents the model estimation results. Section 6 discusses policy recommendations. Finally, Section 7 concludes with key insights and implications.

2. Literature review

This section synthesizes existing literature on user preferences towards V2G programs, focusing on the willingness to adopt, key determinants (i.e., drivers and barriers), and the influence of user characteristics on preferences. Research in this area has expanded in recent years, particularly through discrete choice experiments that examine V2G contract preferences. Refer to Table A.1 in Appendix A for an overview of key findings from previous choice experiments.

2.1. Willingness to participate

Early studies, conducted in the United States, analyzed stated preference data from 2009, comparing conventional gasoline vehicles with V2G-enabled EVs, each with specific EV attributes and V2G contract requirements (Parsons et al., 2014; Hidrue and Parsons, 2015). These studies found that the financial compensation requirements for V2G far exceeded feasible market rates (Kempton and Tomić, 2005), making V2G unattractive to most consumers and projecting a low market share even under optimistic battery cost scenarios. However, given the rapid advancements in EV technology and infrastructure, these findings may no longer accurately reflect contemporary consumer sentiment.

More recent research provides updated insights, though most studies focus on valuing V2G contract attributes—such as financial compensation, guaranteed driving range, plug-in time, battery degradation, and contract duration—rather than directly measuring willingness to adopt. Initial findings suggest that the willingness varies across regions. In some countries, such as Germany, Switzerland, Norway, and Finland, interest in V2G is found to be relatively high among both EV and non-EV drivers (Geske and Schumann, 2018; Noel et al., 2019c; Kubli et al., 2018). Conversely, in other countries, such as Slovakia, Denmark, Sweden, and Iceland, interest remains low (Kajanova et al., 2021; Noel et al., 2019c). In the Netherlands, where studies have focused solely on EV users, findings are mixed. While some studies report strong overall willingness to participate (Zonneveld, 2019; van Heuveln et al., 2021), other research suggests that Dutch EV drivers remain hesitant under current recharging conditions but show significantly greater willingness in a fast-charging context (Huang et al., 2021). However, it remains unclear whether these regional differences reflect actual contextual variations in consumer preferences or stem from methodological differences and study design.

While valuable insights into V2G preferences have emerged, direct assessments of the willingness to adopt remain scarce, and findings for the Dutch context are both limited and conflicting—despite initial evidence that local conditions shape adoption. These inconsistencies underscore the complexity of V2G adoption and highlight how context, target populations, and research design shape outcomes. For example, some studies have examined V2G adoption in conjunction with EV purchase decisions (Parsons et al., 2014; Noel et al., 2019c), while others, including those in the Dutch context (Huang et al., 2021; Zonneveld, 2019), have analyzed V2G preferences separately.[2]

2.2. Key determinants: drivers and barriers

Key determinants influencing user willingness to adopt V2G have been identified across both the referenced choice experiments in Section 2.1, as well as complementary qualitative work (e.g., Bakhuis et al., 2025a; Gschwendtner et al., 2021; Kester et al., 2018; Noel et al., 2019a; Sovacool et al., 2017, 2018b, 2019; van Heuveln et al., 2021).

The primary motivational drivers can be grouped into three categories: (i) financial benefits, (ii) environmental motivations, and (iii) electricity grid support. *Financial benefits* arise from the potential for EV owners to generate revenue by providing electricity grid services[3], helping offset disadvantages or provide additional income—reducing EV ownership costs (NREL, 2017). *Environmental motivations* are primarily linked to V2G's role in integrating renewable energy and promoting EV adoption, thereby reducing emissions in both the electricity and transport sectors. This contributes to climate change mitigation[4] (Sovacool and Hirsh, 2009; Yilmaz and Krein, 2012) while also offering additional benefits, such as improving local air quality (Ferrero et al., 2016; Campello-Vicente et al., 2017). Additionally, V2G may decrease

[2] We adopt the latter approach to isolate V2G-specific preferences from broader EV attributes (e.g., vehicle price or range), avoiding confounding effects and ensuring clearer insights for early-stage V2G policy recommendations.

[3] Potential grid services include peak shaving, load balancing, frequency regulation, and energy arbitrage. Revenue potential varies based on different factors such as service type, plug-in time, and battery capacity, with estimates ranging from $2000 and $4000 *per* year (Kempton and Tomić, 2005; White and Zhang, 2011; Hidrue and Parsons, 2015; Noel et al., 2019c), to be divided among the stakeholders.

[4] It may appear that in the context of multi-mode interaction and inter-niche competition, V2G technology is highly dependent on EVs, while EVs are not reliant on V2G. However, V2G has the potential to reshape the relationship between renewable energy generation and EVs. By acting as a bridging (or sector coupling) technology, V2G enables renewable energy sources to benefit from EVs as well. This transforms their relationship from a unilateral dependency to a mutually beneficial, bilateral partnership.

reliance on stationary (grid-scale) batteries (Brown et al., 2018), reducing demand for scarce resources like lithium. *Electricity grid* support stems from V2G's capacity to alleviate grid congestion, enhance grid stability (e.g., by reducing peak loads), and improve energy distribution efficiency (Štogl et al., 2024)—particularly in markets with high renewable penetration, such as the Netherlands (Netbeheer Nederland, 2023). By strengthening grid reliability, V2G can help prevent disruptions like power outages and restrictions on new renewable energy connections, while also potentially lowering grid management costs.

Aside from these advantages, three main user-related barriers to V2G adoption have been widely reported: (i) loss of flexibility, (ii) battery degradation, and (iii) data privacy and security. *Loss of flexibility* arises from added V2G functions to EVs beyond transportation, potentially restricting users' freedom and convenience (Schmalfuss et al., 2015; Will and Schuller, 2016). Key concerns include uncertainty about the vehicle's state of charge (affecting driving range), mandatory minimum plug-in times, and third-party control over charging functions. These factors may undermine users' sense of autonomy, which is crucial for most vehicle users (Buys et al., 2012; Berg et al., 2015). *Battery degradation* is another concern, as increased (dis)charging cycles could affect battery health, exacerbate range anxiety, and accelerate vehicle depreciation (Pevec et al., 2019, 2020; Peterson et al., 2010; Dubarry et al., 2017; Bhoir et al., 2021). While research remains inconclusive about the actual extent of degradation[5], negative perceptions may persist, deterring participation due to concerns over reduced driving range, higher replacement costs, and increased ownership expenses (Sovacool et al., 2017; Kester et al., 2018; Gschwendtner et al., 2021). *Data privacy and security* concerns stem from the need to share vehicle and usage data with third-party operators such as utilities, manufacturers, or aggregators. Users may be hesitant to disclose private information—such as location and charging patterns—due to fears of data misuse or security vulnerabilities (Han and Xiao, 2016; Carre et al., 2018). Research indicates a low public trust with similar technologies, such as smart meters (Asghar et al., 2017).

While the drivers and barriers of V2G adoption are well-documented, uncertainty remains about how users value these factors, and which have the greatest influence. Former research broadly suggests that users are more likely to participate when their mobility needs remain largely uncompromised—whether through fast-charging availability (Huang et al., 2021; Zonneveld, 2019; Kajanova et al., 2021) or contract structures that impose little required plug-in time and guarantee sufficient charge levels (Geske and Schumann, 2018; Kubli et al., 2018). However, many studies infer rather than directly measure the impact of these determinants. For instance, Huang et al. (2021) found that discharging cycles were the most influential contract attribute, emphasizing concerns over battery degradation. Former findings also vary, with some studies emphasizing financial incentives as crucial (van Heuveln et al., 2021; Huang et al., 2021), while others suggesting the adoption potential to be high even without them, given the flexibility loss and battery concerns are addressed (Geske and Schumann, 2018).[6] These inferences and inconsistencies highlight the need for further research to determine the strongest influences on V2G participation.

2.3. User characteristic factors

Although research on V2G consumer preferences has grown, insights on the influence of individual user characteristics remains limited. Some initial insights have emerged regarding age, gender, income, driving patterns, and charging behavior. Younger individuals tend to be more open to V2G adoption (Noel et al., 2019c). Gender differences indicate that men are generally more willing to participate than women (Zonneveld, 2019). Income has shown minimal influence on adoption, though higher-income individuals tend to perceive lower utility from V2G than lower-income users (Zonneveld, 2019). Additionally, high daily mileage discourages participation due to concerns relating to vehicle availability (Geske and Schumann, 2018; Noel et al., 2019c). The role of charging location remains ambiguous with some studies suggesting that home charging facilitates V2G adoption (Huang et al., 2021), while others find no significant correlation (Zonneveld, 2019).

The current study aims to contribute to the literature and address the existing gaps by directly analyzing stated willingness to adopt V2G, examining how key drivers and barriers influence this willingness, and exploring the role of a broad range of user characteristics. By including a broad sample of car users—including both EV and non-EV drivers[7]—this research provides deeper insights into the Dutch context, where the previous studies have solely focused on EV users. It also provides a broader perspective on V2G preferences across diverse user groups while exploring a wider range of user characteristics than previously studied. Additionally, this research seeks to validate or challenge prior findings, enhancing the overall understanding of V2G preferences.

3. Experiment design and data collection

The data for this research was collected through an online stated preference survey created in Qualtrics. The survey included a choice experiment with twelve choice questions, along with approximately forty-five additional questions covering stated intentions and user characteristics. It was administered in Dutch to increase understanding and engagement among respondents in the Netherlands.

Data collection was primarily managed by a third-party provider (Dynata[8]), which ensured a diverse respondent base across age, gender, education, and car type. The final sample comprised 1018 participants, all of whom hold a valid driver's license, reside in the Netherlands, and have regular access to at least one car (owned, leased, rented, or shared).

This research is part of a broader effort to analyze the V2G dataset. Specifically, it examines participants' stated intentions regarding likelihood of participation and key determinants—drivers and barriers—influencing their decisions. Meanwhile, a separate study analyzes the choice question data to assess V2G contract attribute valuation (Bakhuis et al., 2025b). Using a latent class model, that study identifies four distinct user groups based on contract preferences.

By separately exploring stated intentions (self-reported ratings and rankings) and stated preferences (derived from the choice experiment), the two studies retain distinct scopes while complementing each other. Together, they provide a more comprehensive understanding of V2G preferences by linking participation likelihood and its underlying

[5] The impact of V2G on battery health remains inconclusive. Some studies report a negative impact (Peterson et al., 2010; Dubarry et al., 2017; Bhoir et al., 2021), while others suggest that improved battery management through V2G could mitigate these effects or even enhance battery longevity (Wang et al., 2016; Debnath et al., 2014; Ortega-Vazquez, 2014; Thompson, 2018). Regardless of actual degradation, persistent negative perceptions may still discourage participation.

[6] Will and Schuller (2016) had similar findings for smart charging in the German context.

[7] Including both EV and non-EV drivers is particularly relevant, as European regulations mandate all new car sales be zero-emission by 2035, with the Netherlands targeting 2030 (European Commission, 2023). Understanding both groups' preferences helps capture more realistic future V2G user preferences, as early EV adopters may not reflect broader trends. Our large and balanced sample ensures EV driver preferences remain accurate, enabling meaningful comparisons between user segments, while maintaining the validity and robustness of our findings.

[8] Dynata is a global market research company that connects researchers with a diverse pool of survey participants for consumer data collection. They compensate respondents and check for representativeness in their datasets.

determinants to contract attribute valuation.[9]

3.1. Survey design

The survey was structured into four parts: (i) introduction, (ii) choice questions, (iii) intentions and attitudes, and (iv) personal, household, and car use characteristics. In the first part, respondents received background information on the V2G innovation, covering its bi-directional charging capabilities, potential role in grid stability and environmental pollution reduction, and the financial compensation offered to EV owners for third-party battery management.

The second part featured a series of choice questions. Each question required respondents to choose between two hypothetical V2G contracts, each defined by four attributes varied at three levels: monthly financial compensation (€40, €90, €140), guaranteed minimum driving range (25 km, 75 km, 125 km), minimum plug-in time (2, 5, or 8 hours per day), and additional annual battery degradation[10] (1%, 2%, 3%). Each contract included two default features. Firstly, by default, the car switches to V2G when plugged in, though users can opt to solely charge their vehicle ("immediate charge") via a phone application. Secondly, the same application tracks plugged-in hours during peak times, with non-compliance with the monthly average plug-in time resulting in no reimbursement for that month. While not central to this study's analysis, these questions provide crucial context for subsequent responses assessing participation likelihood and evaluating key drivers and barriers. By familiarizing participants with V2G functionality and realistic contract structures, they highlighted potential barriers, outlined financial trade-offs, and set realistic compensation expectations.

The third part, central to this study, captured participants' likelihood of adopting V2G and the key determinants. As with most other questions, responses were measured on a five-point scale with a neutral midpoint. Participants rated their likelihood of engaging in a V2G program on a scale from (1) very unlikely to (5) very likely. The importance of key drivers—financial, environmental, and electricity grid reasons—was assessed ranging from (1) not important at all to (5) very important. Similarly, concerns about key adoption barriers—battery degradation, data privacy, and loss of flexibility—were rated from (1) not concerned at all to (5) very concerned. Additionally, this part also explored participants' views on environmental sustainability, enthusiasm for new technologies, inclination to use smart home technologies, attitude towards their car as a symbol of freedom and mobility, and familiarity with V2G.

The final section gathered detailed information about respondents' personal characteristics. These included socio-demographic factors—such as gender, age, education, income, and employment status—as well as household characteristics—such as size, composition, presence of children, housing type, and living area—and car usage details—including vehicle type, number of cars, car access type (e.g., ownership, leasing, or sharing), driving frequency, and how often vehicles were used for various purposes, such as commuting or leisure.

3.2. Analytical approach

The research question comprises two key aspects: (i) understanding the likelihood of participation in V2G programs and (ii) identifying the main drivers and barriers influencing that decision. The second aspect complements the first by shedding light on the primary factors that either encourage or discourage participation. To assess the likelihood of participation, we analyzed responses to the survey question where participants directly rated their likelihood of participating. To examine the primary drivers and barriers, we converted participants' ratings of the three drivers and three barriers into rankings, while excluding indecisive respondents to gain clearer insights. Below, we explain our approach and rationale.

Given the novelty of V2G, we sought to capture clear preferences while minimizing ambiguity by avoiding forced rankings of factors respondents might feel uncertain about. Instead, as research indicates that ratings effectively capture respondent indifference and ambivalence, we collected ratings data (Mackenzie, 1993; Roe et al., 1996; Lifke and Syroid, 2016). To identify the most influential determinant, we assumed that the highest rating—given without explicit ranking instructions—represented the respondent's primary driver or barrier. Participants who assigned their highest rating to multiple drivers or barriers were excluded from this part of the analysis, as they did not exhibit a distinct preference.[11]

Refining and filtering data for clarity is a standard practice in choice modeling and preference analysis (Sheela and Mannering, 2020; Barbour et al., 2021). Specifically, converting ratings into rankings is a recognized practice (Mackenzie, 1993; Roe et al., 1996; Stevens et al., 1997; Agarwal, 2016; Layton and Lee, 2006). Moreover, research has demonstrated that ranking and rating methods yield highly comparable preference structures (Moors et al., 2016), supporting the validity of this methodological approach.

Following this refinement, the final sample sizes for the three separate choice models are as follows: Likelihood of participating (n =

Table 1
Summary statistics for the full sample (n = 1018).

Variable	Categories	Percentage of respondents
Age	18–24	4%
	25–30	9%
	31–40	17%
	41–50	17%
	51–60	19%
	61–65	10%
	>65	24%
Gender	Male	53%
	Female	47%
	Other	0%
Education[a]	Primary school	1%
	VMBO or MAVO	15%
	HAVO or VWO	7%
	Secondary vocational education	23%
	Bachelor of applied science	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%

[a] VMBO or MAVO are lower levels of high school and HAVO and VMBO are highest levels of high school in the Netherlands.

[9] The connection between these studies emerges from comparing how user characteristics influence V2G preferences—a shared focus in both studies, each incorporating a broad and comparable set of user characteristics. Future research could (i) link participation likelihood to latent preference classes, (ii) connect contract valuation to underlying drivers and barriers, and (iii) explore synergies or gaps between stated intentions and revealed preferences.

[10] In the survey we noted that the typical annual EV battery decline is 1–2%, with batteries usually replaced at 70–80% capacity.

[11] Methodologically, tied rankings can complicate the modeling process, as the employed mixed logit models assume a clear order of preferences (Statacorp, 2023). Ties indicate a respondent's inability or reluctance to prioritize among options, introducing ambiguity that can reduce analytical precision and affect the reliability of preference estimations.

1018—using the full dataset), main driver (n = 518), and main barrier (n = 434). Table 1 presents summary statistics for key respondent attributes in the full sample, demonstrating the representativeness and diversity of the data. These statistics align with the Dutch car driver benchmarks (CBS, n.d.), and crucially, we obtained a broad distribution of respondents across categories, ensuring a sufficient number of responses in each to measure preferences significantly. A comparison of these attributes in the subsamples used for analyzing the drivers and barriers shows a close match to the full sample—typically varying by only 1%–3% (refer to Table B.1 in Appendix B for a comparison of the samples). This consistency reinforces the validity and robustness of the models and supports meaningful comparisons across them.

Finally, regarding the validity of our sample sizes; while no strict minimum exists for discrete choice experiments or preference analysis, a common benchmark suggests at least 100 respondents for robust estimates (Pearmain and Kroes, 1990; de Bekker-Grob et al., 2015).[12] Our sample sizes of 1018, 514 and 434 comfortably exceed this threshold. Further supporting their reliability, our dataset—including subsets—is larger than prior Dutch V2G choice experiments, such as Zonneveld (2019) with 97 respondents and Huang et al. (2021) with 148. Additionally, our samples are also comparable to or exceed those from previous V2G studies in other contexts, including Kajanova et al. (2021) with 289 and Geske and Schumann (2018) with 611. These comparisons underscore the robustness of both our full dataset and subsamples for analyzing V2G preferences.

4. Methods

Several well-established methods exist for analyzing ratings and rankings data, including multinomial logit (MNL) models, latent-class (finite mixture) models, and random parameters logit models (Savolainen et al., 2011; Mannering and Bhat, 2014; Mannering et al., 2016). In this study, we employed two types of random parameters logit models.

For our first objective—investigating factors influencing willingness to participate in V2G—we utilized a random parameters ordered probit model since it is suitable for analyzing the ordered response data (Greene, 1997; Washington et al., 2020; Mannering et al., 2016). For our second objective—identifying main drivers and barriers—standard ordered-response modeling approaches were unsuitable due to the categorical and non-ordinal nature of the rankings data. Instead, we employed two separate random parameters multinomial logit (or mixed logit) models: one for drivers and one for barriers (Hensher and Greene, 2003).

These modeling choices offer several advantages. Although computationally more demanding and complex to interpret, random parameters models provide a significantly better model fit and predictive accuracy compared to multinomial logit models, leading to more robust estimation results (Hensher and Greene, 2003; Train, 2009; McFadden and Train, 2000).[13] By incorporating random parameters, these models account for unobserved heterogeneity in individual preferences, acknowledging that participants may respond differently to explanatory variables due to unobserved reasons. This is particularly crucial when studying emerging technologies such as V2G, where user attitudes, prior experiences, and contextual influences can vary significantly (Barbour et al., 2019a, 2019b; Barbour and Mannering, 2023).

These approaches are well-established in transportation research, particularly for analyzing crash-injury severity (Anastasopoulos and Mannering, 2011; Behnood & Mannering, 2015, 2016; Eluru et al., 2008; Kim et al., 2013; Milton et al., 2008; Morgan and Mannering, 2011; Venkataraman et al., 2013; Behnood et al., 2014) and new technology adoption (Barbour et al., 2019a, 2019b; Barbour and Mannering, 2023). However, their application in V2G research remains limited (see Table A.1 in Appendix A). Notably, prior V2G studies conducted in the Netherlands have primarily relied on basic multinomial logit models, often incorporating only a narrow set of sociodemographic variables (e.g., gender, income, age).

4.1. Statistical choice modeling approaches

4.1.1. Ordered probit model with random parameters

For this study, we begin with defining an unobserved variable, z, as a linear function of explanatory variables,

$$z_i = \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{1}$$

where $\mathbf{X}_i$ is a vector of explanatory variables that determines the discrete ordering of observation i, $\boldsymbol{\beta}$ is a vector of estimable parameters, and ε_i is a disturbance term. Equation (1) is further used to define observed ordinal data, y_i:

$$y_i = 1 \text{ if } z_i \le \mu_0 \tag{2}$$

$$= 2 \text{ if } \mu_0 < z_i \le \mu_1$$

$$= 3 \text{ if } \mu_1 < z_i \le \mu_2$$

$$= 4 \text{ if } \mu_2 < z_i \le \mu_3$$

$$= 5 \text{ if } z_i \ge \mu_3$$

where 1 = very unlikely, 2 = unlikely, 3 = neutral, 4 = likely, and 5 = very likely, and μ's are considered estimable parameters (also known as thresholds) that define y_i and are estimated together with parameters $\boldsymbol{\beta}$. To determine the probability of the five predefined ordered responses for each observation i, an assumption on the distribution of ε_i in Equation (1) was made. In this case, an ordered probit model is warranted if ε_i is assumed to be normally distributed across the collected responses. The ordered category selection probabilities can be defined as (Washington et al., 2020),

$$P(y=1) = \Phi(-\boldsymbol{\beta}\boldsymbol{X}_i) \tag{3}$$

$$P(y=2) = \Phi(\mu_1 - \boldsymbol{\beta}\mathbf{X}_i) - \Phi(-\boldsymbol{\beta}\mathbf{X}_i)$$

$$P(y=3) = \Phi(\mu_2 - \boldsymbol{\beta}\mathbf{X}_i) - \Phi(\mu_1 - \boldsymbol{\beta}\mathbf{X}_i)$$

$$P(y=4) = \Phi(\mu_3 - \boldsymbol{\beta}\mathbf{X}_i) - \Phi(\mu_2 - \boldsymbol{\beta}\mathbf{X}_i)$$

$$P(y=5) = 1 - \Phi(\mu_3 - \boldsymbol{\beta}\mathbf{X}_i)$$

where $\Phi(.)$ is defined as the cumulative normal distribution.

Considering the model interpretation, a positive value of $\boldsymbol{\beta}$ indicates that an increase in $\mathbf{X}_i$ will increase the probability of having the highest response (very likely) and will decrease the probability of having the lowest response (very unlikely). Marginal effects are estimated to determine the effect that the explanatory variables have on the dependent variable (as written in Washington et al., 2020),

$$\frac{P_i(y=n)}{\partial \mathbf{X}_i} = [\,\Phi(\mu_{n-1} - \boldsymbol{\beta}\mathbf{X}_i) - \Phi(\mu_n - \boldsymbol{\beta}\mathbf{X}_i)]\boldsymbol{\beta} \tag{4}$$

where $P(y=n)$ is defined as the probability of outcome response n, μ

[12] Louviere and Lancsar (2009) noted that as few as 20 respondents can suffice for reliable model estimation, while noting that larger sample sizes are necessary for meaningful post hoc analyses and identifying covariate effects.

[13] The standard multinomial logit (MNL) model assumes independence of irrelevant alternatives (IIA), meaning choice probabilities between any two alternatives remains constant despite the presence of additional options—an assumption often unrealistic in real-world decision-making. Random parameters logit models address this limitation by allowing for flexible substitution patterns across choices and capturing correlations in unobserved factors, thereby better accounting for individual-specific preference heterogeneity.

represents the thresholds, and $\phi(.)$ is considered the standard normal density. In the current research, unobserved heterogeneity is addressed by estimating a random parameters model using,

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \varphi_i \tag{5}$$

where $\boldsymbol{\beta}_i$ is defined as a vector of observation parameters and φ_i is assumed to be a randomly distributed term.

4.1.2. Multinomial logit model with random parameters

In order to arrive at an estimable statistical model, a function determining the greatest driver (financial, environmental, or electricity grid) or the greatest barrier (battery degradation, data privacy and security, and loss of flexibility) to V2G participation was defined as (Washington et al., 2020),

$$\mathrm{F}_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} + \varepsilon_{in} \tag{6}$$

where F_{in} is a function that determines the probability of respondent n selecting the main driver or barrier i, $\boldsymbol{\beta}_i$ is a vector of estimable parameters for corresponding to discrete response i, $\mathbf{X}_{in}$ is defined as a vector of explanatory variables affecting the probability of response i for respondent n, and ε_{in} is a disturbance term. As the disturbance terms are defined as extreme-valued distributed, a standard multinomial logit model results as (McFadden, 1981),

$$\mathrm{P}_n(i) = \frac{EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_{\forall I} EXP[\boldsymbol{\beta}_I \mathbf{X}_{in}]} \tag{7}$$

where $\mathrm{P}_n(i)$ is the probability of respondent n selecting answer i, and I is the set of possible responses.

Unobserved heterogeneity is addressed by allowing one or more parameter estimates in the vector $\boldsymbol{\beta}_i$ to vary across respondents. A normal distribution is assumed for these varying parameters, and Equation (7) is reformulated to account for this variation as (Washington et al., 2020),

$$\mathrm{P}_n(i) = \int_X P_n(i) f(\boldsymbol{\beta}_i \mid \boldsymbol{\varphi}_i) d\boldsymbol{\beta}_i \tag{8}$$

where $f(\boldsymbol{\beta}_i \mid \boldsymbol{\varphi}_i)$ is the density function of $\boldsymbol{\beta}_i$, $\boldsymbol{\varphi}_i$ is a vector of parameters describing the density function (mean and variance), with other terms previously defined. This formulation yields the random parameters logit model (or mixed logit model).

4.1.3. Model interpretation

The interpretation of both model types is similar. The ordered probit model estimates the overall likelihood of participating in V2G, while the mixed logit models assess the likelihood of selecting specific categories, such as a main driver or barrier.

The estimated parameter ($\boldsymbol{\beta}_i$) for each indicator (dummy) variable—representing user characteristics coded as binary values (e.g., gender coded as 1 for female and 0 for male)—indicates how each specific user characteristic (coded as “1”) influences V2G preferences relative to the reference group (coded as “0”). For example, a negative estimate for the gender indicator in the ordered probit model suggests that identifying as female decreases the participation likelihood relative to males, whereas a positive estimate would indicate an increased likelihood.

To aid model interpretation, average marginal effects (averaged over all observations) are computed and reported.[14] These marginal effects indicate the effect of a one-unit change in an independent variable on the dependent variable. For the binary indicator variables, this effect represents the change in response probability when the variable shifts from 0 to 1 (Washington et al., 2020).

For random parameters—which capture unobserved preference heterogeneity in respondent preferences—we report the mean and standard deviation. To determine the percentages of respondents with higher or lower likelihoods, we calculate the proportion of the distribution that falls above or below zero, assuming a normal distribution. For example, in the ordered probit model, the “mature age” indicator has a mean of −0.25 and a standard deviation of 0.73. To find the percentage of respondents likely to participate, we calculate how many standard deviations zero is from the mean, which gives a Z-score[15] of approximately 0.34. Using a standard normal distribution table or calculator, this Z-score indicates that about 63% of the distribution falls below zero (indicating a lower likelihood of participation) and the remaining 37% falls above zero (indicating a higher likelihood).

4.2. Modeling process and estimation

For all three models, we employed a stepwise approach, adding one parameter at a time and testing its significance using likelihood ratio tests. Only statistically significant parameters that improved the model fit were retained. For each model, the null hypothesis that fixed and random parameters models are the same was rejected with over 95% confidence (based on the likelihood ratio test). Therefore, only the random parameters model results are presented and discussed in Section 5.

All models were estimated using simulated maximum likelihood, as the logit formula requires numerical integration over the distribution of (random) parameters due to its non-closed-form nature (Train, 2009; Washington et al., 2020).[16] To enhance estimation, we used 1000 Halton draws per model, a number shown to provide accurate parameter estimates (McFadden and Ruud, 1994; Bhat, 2003; Milton et al., 2008; Anastasopoulos and Mannering, 2009; Behnood and Mannering, 2016).

In this study, the parameter distribution is assumed to be normal, which is commonly applied in random parameters models (Behnood and Mannering, 2016; Chen et al., 2018; Weng et al., 2018; Ghaisi et al., 2019). Additionally, initial tests with alternative distributions—such as log-normal, uniform, and exponential—did not yield statistically superior estimation.

5. Results

In this section, we begin by presenting the descriptive statistics of the dependent variables relevant to answering our two-part research question on the (i) likelihood of participation, and complementarily, (ii) the main drivers and barriers. The subsequent subsections present model estimation results for each model separately, with a final subsection summarizing the overarching findings. Each model description highlights key findings rather than discussing each variable in detail. For a comprehensive overview, readers are directed to the corresponding tables for each model and Section 4.1.3 for model interpretations.

[14] Marginal effects are computed using the Nlogit software suite, which first estimates the predicted probability of each outcome based on the model coefficients. The software then perturbs an independent variable (e.g., shifting from 0 to 1 for binary variables or increasing by one unit for continuous variables) while keeping all other variables constant. The resulting difference in probabilities represents the marginal effect.

[15] $Z = \frac{0 - Mean}{Standard\ Deviation}$

[16] All three models were estimated using the Nlogit (LIMDEP) software (Greene and Hensher, 2003).

5.1. Descriptive statistics

The descriptive statistics for the likelihood of participation in V2G for the full sample are presented in Fig. 1. The average rating for participation likelihood is 3.15, with a standard deviation (SD) of 1.16. The results indicate that most respondents reported being either likely (31%) or very likely (11%) to participate in V2G programs, with a significant portion remaining neutral (32%). In contrast, fewer of them expressed being unlikely (14%) or very unlikely (12%).

The descriptive statistics for the main drivers and barriers for the full sample are presented in Figs. 2 and 3, respectively, revealing similar trends in both categories. Among the drivers, the financial driver category had the highest average score of 3.59 (SD = 1.08), followed by the electricity grid driver at 3.47 (SD = 1.10), and the environmental driver at 3.37 (SD = 1.14). For the barriers, loss of flexibility had the highest average score of 3.63 (SD = 0.97), followed by battery degradation concerns with an average score of 3.40 (SD = 0.92), and data privacy and security concerns, which averaged 3.18 (SD = 1.06).

Finally, we present the distribution of dependent variables across the separate models. In the ordered probit model assessing likelihood to participate, we use the complete sample (n = 1018), so the distribution matches that shown in Fig. 1. For the mixed logit models, however, we focus on subsamples that include only decisive participants with a clear preference (as described in Section 3.2). For the main drivers (n = 518), the distribution is presented in Fig. 4, showing that most respondents prioritize financial reasons (49%) as their primary motivator for V2G engagement, with nearly equal numbers prioritizing environmental (25%) and electricity grid (26%) considerations. For the main barriers (n = 434), Fig. 5 shows that the largest fraction of respondents identifies loss of flexibility (55%) as their primary barrier, followed by battery degradation concerns (27%), with the smallest group indicating data privacy and security (18%) as the main barrier to V2G participation.

5.2. Likelihood of participating inV2G

Summary statistics for variables found to be statistically significant in the ordered probit model with random parameters for the participation likelihood are presented in Table 2. The estimation results and corresponding marginal effects of the model are presented in Table 3.

Regarding *socio-demographic factors*, gender is a key determinant, with females being generally less likely to participate, which aligns with research on gender differences in risk perception (Abay and Mannering, 2016; Solá, 2016; O'Connor et al., 1999; Denton, 2002; Viscusi and Zeckhauser, 2006; Kellstedt et al., 2008) and mobility patterns (Dunckel-Graglia, 2013; Mazumder and Pokharel, 2019; Sovacool et al., 2018a; Kawgan-Kagan, 2015; Mahadevia and Advani, 2016; Zheng et al., 2016; Basarić et al., 2016). Age also plays a role—both younger (≤ 25 years) and older individuals (≥ 62 years) are less likely to participate, though older respondents display significant preference heterogeneity (64% less likely, 37% more likely). Income is also important—lower-income individuals (≤ €60.000/year) are generally less likely to participate, while displaying heterogeneous preferences (68% less likely, 32% more likely); meanwhile higher-income individuals (≥ €100.000/year) show greater participation likelihood. Education follows a similar pattern, with higher-educated individuals (≥ bachelor of applied science) more inclined to participate in V2G. Overall, these trends suggest that highly educated males aged 25 to 62 are the most likely participants, consistent with patterns in transport innovations such as automated vehicles and shared mobility (Shin et al., 2015; Lavieri et al., 2017; Shaheen et al., 2014; Woodcock et al., 2014; Dias et al., 2017).

Considering *household factors*, respondents without children in the household or those living in apartments are less likely to participate. Conversely, respondents with home parking access show higher participation likelihood, highlighting the importance of charging convenience. Those using renewable energy at home are also more likely to engage in V2G, potentially related to their environmentally conscious mindset and openness to new technologies (Jabeen et al., 2019; Qazi et al., 2019; Zeng et al., 2022). These findings align with EV adoption research, which emphasizes the importance of charging infrastructure in reducing range anxiety, alleviating perceived mobility restrictions, and reinforcing positive EV subjective norms (White et al., 2022; Dixon et al., 2020; Egbue et al., 2017).

Turning to the *car use factors*, respondents primarily driving fossil fuel vehicles[17] are less likely to participate in V2G, consistent with research suggesting that familiarity with EVs increases confidence and reduces EV-related concerns (Bühler et al., 2014; Gschwendtner and Krauss, 2022). In contrast, those involved in car sharing show higher participation likelihood, aligning with research showing that V2G-enabled carsharing is preferred over traditional EV-sharing or fossil-fuel car sharing (Gschwendtner and Krauss, 2022; Schlüter and Weyer, 2019; Cartenì et al., 2016; Paundra et al., 2017). Driving frequency also plays a role—less frequent drivers, including those without a daily commute or driving fewer than three days per month, are less likely to participate. Conversely, frequent drivers (≥ 5 days/week) show higher participation likelihood, though leisure drivers display heterogeneous behavior (69% more likely, 31% less likely). However, frequent long-distance drivers (≥ 11 days/month, 50+ km) are more hesitant, likely due to range concerns. These findings suggest that routine drivers are more inclined toward V2G, whereas long-distance drivers may be more hesitant.

Concerning the *attitude and preference factors*, respondents concerned about EV range are generally less likely to participate—while displaying heterogeneous behavior (70% less likely, 30% more likely)—aligning with previous findings on range anxiety towards EVs diminishing willingness to participate in V2G (Geske and Schumann, 2018).[18] Similarly, those who do not prioritize environmental sustainability are also less likely to participate, with significant heterogeneity (83% less likely, 17% more likely). This heterogeneity suggests that a subset of environmentally conscious individuals may still find other motivating factors insufficient or the barriers too formidable to engage in V2G. Lastly, respondents who view their car as unimportant for freedom and mobility[19] are less inclined to adopt V2G.

5.3. Main drivers forV2G participation

Summary statistics for variables that were statistically significant in the mixed logit model for the main drivers relating to V2G participation are presented in Table 4. The estimation results and corresponding marginal effects of the model are presented in Table 5.

Regarding the *socio-demographic factors*, older respondents (≥ 65 years) are less likely to prioritize financial reasons for V2G participation. Income also plays a role—lower-income individuals (≤ €50.000/year) are generally more likely to prioritize financial drivers, though behavior is heterogeneous (61% more likely, 39% less likely). Similarly, higher-income respondents (≥ €100.000/year) are also more likely to

[17] Note that respondents were asked to assume they owned a V2G-enabled EV in this hypothetical experiment.

[18] Our findings on likelihood of V2G adoption build on those of Geske and Schumann (2018) in several ways. First, our results clarify the role of socio-demographic factors—such as gender, age, and income—which were inconclusive in their study. Second, we find that support for renewables and environmental awareness significantly influence adoption likelihood, whereas these factors were not statistically significant in their model. Finally, our results reveal a more nuanced relationship between driving patterns and willingness to participate in V2G: while high mileage users are found less inclined, frequent short-distance drivers demonstrate a higher willingness.

[19] Notably, the vast majority of respondents place high importance on their car for freedom and mobility, resulting in only a small minority (6%) appearing in the subsample of the main barrier dependent variable. This indicates how entrenched the car-centric road transport system still is.

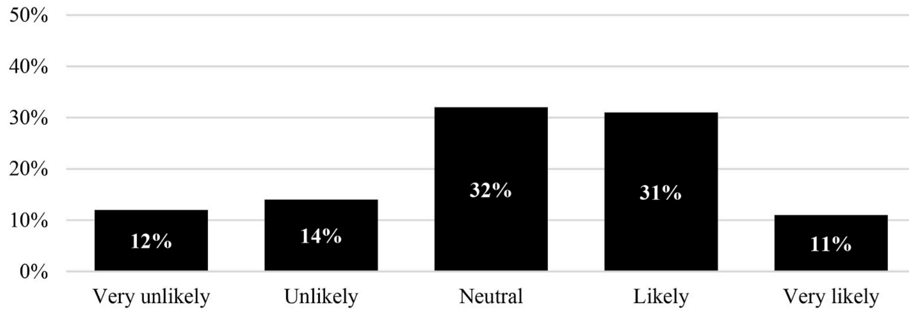

Fig. 1. Descriptive statistics of likelihood of participation in V2G (n = 1018).

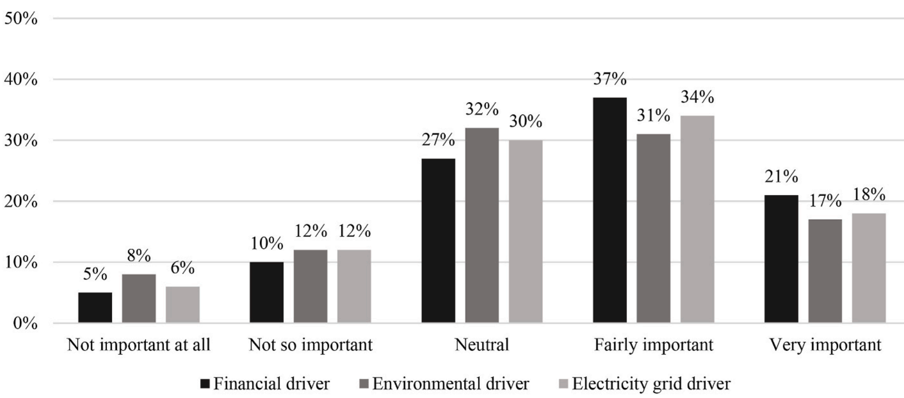

Fig. 2. Descriptive statistics of the drivers (n = 1018).

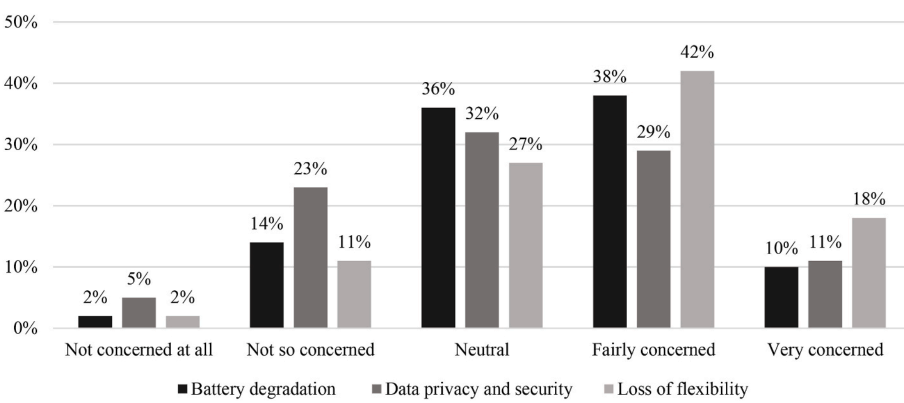

Fig. 3. Descriptive statistics of the barriers (n = 1018).

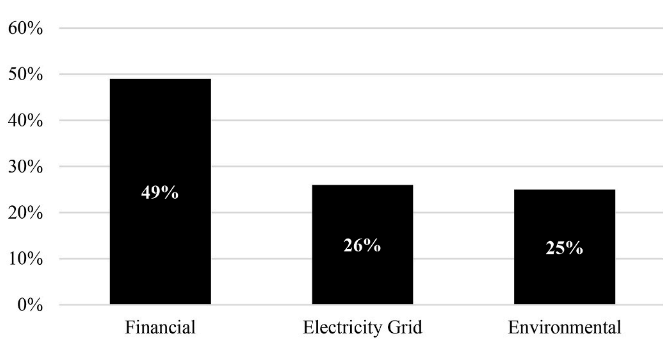

Fig. 4. Primary driver for V2G engagement among decisive respondents (n = 518).

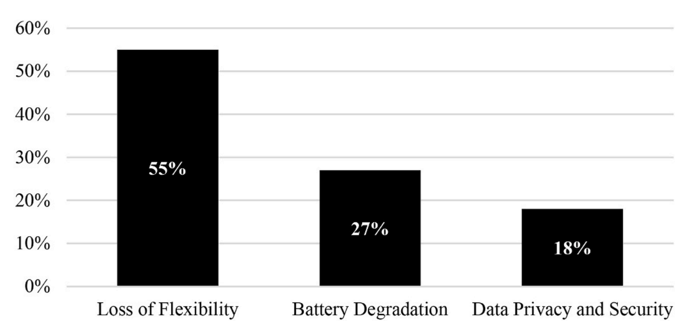

Fig. 5. Primary barrier to V2G engagement among decisive respondents (n = 434).

Table 2
Summary statistics of variables included in the final model estimation of the V2G participation likelihood (n = 1018).

Variable description	Mean	Standard deviation
Socio-demographic factors		
Gender Indicator *(1 if identifies as a female; 0 otherwise)*	0.47	0.50
Younger Age Indicator *(1 if age is 25 years or younger; 0 otherwise)*	0.04	0.20
Mature Age Indicator *(1 if age is 62 years or older; 0 otherwise)*	0.30	0.46
Higher Income Indicator *(1 if household annual income before taxes is €100,000 or more; 0 otherwise)*	0.11	0.31
Lower Income Indicator *(1 if household annual income before taxes is €60,000 or less; 0 otherwise)*	0.63	0.48
Higher Education Indicator *(1 if completed a bachelor of applied science degree or higher; 0 otherwise)*	0.54	0.50
Household factors		
No Children Indicator *(1 if does not have children under the age of 18 in the household; 0 otherwise)*	0.70	0.46
Living Area Indicator *(1 if lives in an urban area; 0 otherwise)*	0.38	0.49
House Type Indicator *(1 if lives in an apartment, including, high-rise; 0 otherwise)*	0.24	0.43
Home Parking Indicator *(1 if has access to parking—private driveway or garage—at home; 0 otherwise)*	0.60	0.49
Renewable Energy Use Indicator *(1 if uses renewable energy sources at home; 0 otherwise)*	0.48	0.50
Car use factors		
Vehicle Type Indicator – Fossil Fuel Vehicle *(1 if mainly drives a fossil fuel vehicle; 0 otherwise)*	0.71	0.46
Car Access Indicator – Car Sharing *(1 if involved in car sharing; 0 otherwise)*	0.11	0.32
Remote Working Indicator *(1 if works remotely less than one day per week; 0 otherwise)*	0.63	0.48
No Commute Indicator *(1 if does not have a daily commute; 0 otherwise)*	0.29	0.45
Low Driving Frequency Indicator *(1 if drives three days per month or less; 0 otherwise)*	0.14	0.35
Car Use Type – Often Commute *(1 if uses their car 5 days or more per week for commuting; 0 otherwise)*	0.27	0.44
Car Use Type – Often Leisure *(1 if uses their car 5 days or more per week for leisure activities; 0 otherwise)*	0.16	0.37
Long Journey Frequency Indicator *(1 if uses their car 11 times or more per month for journeys longer than*50 km; *0 otherwise)*	0.08	0.27
Attitude and preference factors		
Environmental Importance Indicator *(1 if considers environmental sustainability 'not so important' or 'not important at all' in decision-making; 0 otherwise)*	0.15	0.35
Car Attachment Indicator *(1 if car is 'not so important' or 'not important at all' for freedom and mobility; 0 otherwise)*	0.05	0.22
EV Concern Indicator – Driving Range *(1 if generally concerned about EV range; 0 otherwise)*	0.58	0.49

prioritize financial reasons. Regarding education, higher-educated respondents (≥ bachelor of applied science) are more likely to prioritize environmental reasons.

Considering *household factors*, respondents without children in the household are found less likely to prioritize financial reasons for participating, and those living with a partner and children are more inclined to prioritize environmental reasons. This tendency among parents may reflect a heightened environmental consciousness, possibly motivated by concerns about the future their children will inherit (Milfont et al., 2020). Furthermore, urban residents are more likely to be motivated primarily by environmental drivers. Although prior research generally finds minimal rural-urban differences in environmental concern (Berenguer et al., 2005; Huddart-Kennedy et al., 2009; Freudenburg, 1991; Armstrong and Stedman, 2019), these motivations may vary among Dutch residents.

Turning to *car use factors,* EV drivers are found more likely to prioritize environmental drivers, reflecting their heightened environmental awareness (Gschwendtner and Krauss, 2022; Plötz et al., 2014; Helmus et al., 2020; Liao and Correia, 2022; Kramer et al., 2013). Conversely, respondents relying mainly on their cars for transportation are more likely to prioritize financial drivers, possibly to offset flexibility loss. Car sharers are found less likely to indicate financial reasons as their main driver. Akin to EV drivers, these users likely emphasize environmental reasons (Gschwendtner and Krauss, 2022). Furthermore, car owners exhibit higher likelihoods to prioritize environmental reasons. Finally, frequent commuters are more likely to prioritize electricity grid reasons, while those who never work remotely are less likely, focusing more on financial and environmental reasons.

Regarding *attitude and preference factors*, respondents less attached to their car are more likely to focus on financial reasons. Similarly, those unfamiliar with V2G also tend to prioritize financial motivations. Individuals interested in using smart home technologies are found less likely to prioritize financial drivers, while those generally enthusiastic about using new technologies are more likely to participate mainly for environmental reasons. Finally, respondents concerned about the costs of EVs have a higher probability of indicating financial reasons as their main driver. This aligns with Chen et al. (2020)'s[20] argument that V2G could help alleviate financial concerns associated with EV adoption and potentially serve as the "tipping point" incentive.

5.4. Main barriers forV2G participation

Summary statistics for variables that were statistically significant in the mixed logit model for the main barriers relating to V2G participation are presented in Table 6. The estimation results and corresponding marginal effects of the model are presented in Table 7.

Regarding the *socio-demographic factors,* female respondents are generally more likely to have flexibility loss as their main barrier, while displaying heterogeneous behavior (67% more likely, 34% less likely), likely due to established gender differences in mobility patterns and risk perception (Abay and Mannering, 2016). Highly educated individuals (≥ master's degree) are more likely to indicate loss of flexibility as their main V2G barrier, while those with lower education (≤ high school) or income (≤ €40.000/year) prioritize data concerns. These two variables—education and income—are often correlated as high-income earners tend to have higher education levels (Cunningham et al., 2018). Employed individuals are found to have lower probability of having battery degradation as a main concern, while also displaying heterogeneous behavior (72% less likely, 28% more likely).

Considering *household factors,* respondents living with a partner—either with or without children—are more likely to place greater emphasis on battery degradation concerns. Furthermore, those in one-person households are less likely to focus on data concerns. Childless

[20] Chen et al. (2020) use hierarchical regression analysis on the same survey data as Noel et al. (2019c) (five Nordic countries, N = 4762) to examine the impacts of six dimensions relating to socio-demographic, technical, economic, and behavioral factors to investigate EV adoption interest. Among electric mobility attributes, V2G capability and charging time are determined to be the most influential predictors. Furthermore, former EV owners considered V2G to be more important than current EV and conventional car owners, implying that V2G could be the marginal incentive that would be the "tipping point."

Table 3
Random parameters ordered probit model on the likelihood of participating in V2G technology if it was available (n = 1018).[a]

Variable description	Estimated parameters	t-statistic	Marginal effects				
			Very unlikely	Unlikely	Neutral	Likely	Very likely
Constant	2.45	13.66					
μ_{01}	0.82	13.05					
μ_{02}	2.03	25.77					
μ_{03}	3.45	34.19					
Socio-demographic factors							
Random parameters *(Standard deviation of parameter distribution)*							
Mature Age Indicator[b] *(≥ 62 years)*	−0.25 *(0.73)*	−2.64 *(10.90)*	0.025	0.045	0.023	−0.073	−0.020
Lower Income Indicator *(≤ €60.000/year)*	−0.21 *(0.44)*	−2.34 *(9.73)*	0.018	0.036	0.025	−0.060	−0.019
Fixed parameters							
Gender Indicator *(female)*	−0.18	−2.45	0.017	0.032	0.020	−0.052	−0.016
Younger Age Indicator *(≤ 25 years)*	−0.33	−1.66	0.040	0.061	0.017	−0.095	−0.022
Higher Education Indicator *(≥ bachelor of applied science)*	0.13	1.64	−0.012	−0.023	−0.014	0.038	0.012
Higher Income Indicator *(≥ €100.000/year)*	0.27	2.12	−0.021	−0.045	−0.039	0.076	0.029
Household factors							
Fixed parameters							
Children Indicator *(no children)*	−0.18	−2.18	0.016	0.032	0.023	−0.053	−0.017
House Type Indicator *(apartment)*	−0.21	−2.30	0.022	0.038	0.019	−0.062	−0.017
Home Parking Indicator *(has private parking access)*	0.22	2.89	−0.021	−0.039	−0.022	0.063	0.019
Living Area Indicator *(urban area)*	0.28	3.47	−0.024	−0.048	−0.033	0.079	0.026
Renewable Energy Use Indicator *(uses renewables)*	0.17	2.28	−0.016	−0.031	−0.020	0.051	0.016
Car use factors							
Random parameters *(Standard deviation of parameter distribution)*							
Car Use Type – Leisure *(≥ 5 days/week)*	0.28 *(0.55)*	2.63 *(6.03)*	−0.022	−0.046	−0.039	0.078	0.029
Fixed parameters							
Vehicle Type Indicator – Fossil Fuel	−0.34	−4.12	0.028	0.057	0.045	−0.096	−0.034
Car Access Indicator – Car Sharing	0.28	2.25	−0.021	−0.046	−0.041	0.077	0.030
Remote Working Indicator *(≤ 1 day/week)*	−0.28	−3.41	0.024	0.048	0.034	−0.080	−0.027
Commute Indicator *(no daily commute)*	−0.14	−1.56	0.014	0.025	0.0140	−0.041	−0.012
Driving Frequency Indicator *(≤ 3 days/month)*	−0.28	−2.58	0.030	0.050	0.020	−0.080	−0.021
Car Use Type – Commute *(≥ 5 days/week)*	0.23	2.60	−0.020	−0.040	−0.030	0.067	0.023
Long Journey Frequency Indicator *(≥ 11 days/month)*	−0.32	−2.27	0.037	0.058	0.019	−0.091	−0.022
Attitude and preference factors							
Random parameters *(Standard deviation of parameter distribution)*							
EV Concern Indicator – Driving Range	−0.23 *(0.45)*	−3.25 *(9.44)*	0.021	0.041	0.027	−0.068	−0.021
Environmental Importance Indicator *(not important)*	−0.96 *(1.01)*	−9.05 *(9.61)*	0.154	0.166	−0.019	−0.251	−0.050
Fixed parameters							
Car Attachment Indicator *(not attached)*	−0.42	−2.65	0.053	0.077	0.016	−0.120	−0.027
Model fit							
LL *(start)*	−1527.49						
LL *(final)*	−1381.29						
AIC	2824.6						
Halton draws	1000						
Number of observations	1018						

[a] Most survey questions of this type were asked on a five-point scale from 1 (not … at all) to 5 (very …), with neutral at 3.
[b] For a full description of the indicator variable, refer to the corresponding indicator variable in Table 2.

households tend to be most concerned about flexibility loss, possibly due to less structured lifestyles in the absence of childcare responsibilities.

Considering *car use factors*, respondents with regular access to only one car are generally more likely to indicate flexibility loss as their main barrier, while displaying heterogeneous behavior (64% more likely, 36% less likely). EV drivers are less likely to prioritize battery degradation, possibly due to lower range anxiety. Three statistically significant car access groups emerged in the model. First, car sharers are less likely to focus on battery degradation, consistent with research showing they prioritize range and convenience (Gschwendtner and Krauss, 2022; Mueller et al., 2015; Wielinski et al., 2017). Second, business lease drivers are found to prioritize data concerns, likely due to reluctance in sharing personal (e.g., location) data with employers. Third, those who do not own their car(s) are more likely to indicate flexibility loss as their main barrier. This likely stems from car owners heightened concern for preserving their vehicle's value—a behavior known as the "endowment effect" (Kahneman et al., 1991; Morewedge et al., 2021)—making them to place greater emphasis on battery degradation than sharers, leasers or renters. Furthermore, infrequent drivers (≤ 11 days/year) are most concerned about data privacy and security, while those without a daily commute are less likely to be most concerned about battery degradation or flexibility loss, both of which impact EV range.

Turning to the *attitude and preference factors*, environmentally conscious respondents are generally less likely to be most concerned about data privacy and security, though some heterogeneity exists (80% less likely, 20% more likely)—a pattern also seen in lower education and income groups. Additionally, those uninterested in smart home technologies are more likely to cite data privacy and security as their primary barrier. Finally, those familiar with V2G are more likely to indicate battery degradation as the main barrier, possibly due to a awareness of its potential battery health impact or widespread discussion of the issue (Peterson et al., 2010; Bishop et al., 2013). However, this concern may be overstated, as research has not confirmed significant degradation. Moreover, V2G familiarity often stems from discussion rather than practical experience, as commercial implementations remain limited. Ghotge et al. (2022) found that users with actual V2G experience tend to prioritize range and flexibility over battery concerns.

Table 4
Summary statistics of variables included in the final model estimation on the main drivers to participate in V2G (n = 518).

Variable description	Mean	Standard deviation
Socio-demographic factors		
Mature Age Indicator *(1 if age is 65 years or older; 0 otherwise)*	0.20	0.40
Lower Income Indicator *(1 if household annual income before taxes is €50,000 or less; 0 otherwise)*	0.50	0.50
Higher Income Indicator *(1 if household annual income before taxes is €100,000 or more; 0 otherwise)*	0.12	0.32
Higher Education Indicator *(1 if completed a bachelor of applied science degree or higher; 0 otherwise)*	0.56	0.50
Household factors		
Children Indicator *(1 if does not have children under the age of 18 in the household; 0 otherwise)*	0.70	0.46
Household Composition Indicator *(1 if lives with a partner and children; 0 otherwise)*	0.31	0.46
Household Size Indicator *(1 if lives in a one-person household; 0 otherwise)*	0.20	0.40
Living Area Indicator *(1 if lives in an urban area; 0 otherwise)*	0.39	0.49
Electricity Bill Indicator *(1 if monthly electricity bill is €100.- or less on average; 0 otherwise)*	0.53	0.50
Car use factors		
Car as Main Mode Indicator *(1 if uses a car as the main mode of transportation; 0 otherwise)*	0.64	0.48
Vehicle Type Indicator – Electric Vehicle *(1 if mainly drives an electric vehicle; 0 otherwise)*	0.13	0.34
Remote Working Indicator *(1 if never works remotely; 0 otherwise)*	0.53	0.50
Car Access Indicator – Car Owner *(1 if owns their car(s); 0 otherwise)*	0.86	0.35
Car Access Indicator – Car Sharing *(1 if involved in car sharing; 0 otherwise)*	0.11	0.31
Car Use Type – Commute *(1 if uses their car 5 days or more per week for commuting; 0 otherwise)*	0.27	0.44
Attitude and preference factors		
V2G Familiarity Indicator *(1 if never heard of V2G; 0 otherwise)*	0.66	0.47
Car Attachment Indicator *(1 if car is 'not so important' or 'not important at all' for freedom and mobility; 0 otherwise)*	0.06	0.24
Technology Enthusiasm Indicator *(1 if 'fairly enthusiastic' or 'very enthusiastic' towards using new technologies; 0 otherwise)*	0.59	0.49
Smart Home Technology Interest Indicator *(1 if 'fairly interested' or 'very interested' in using smart home technologies; 0 otherwise)*	0.63	0.48
EV Concern Indicator – Initial Costs *(1 if generally concerned about initial costs of electric vehicle; 0 otherwise)*	0.53	0.50
V2G Barrier – Battery Degradation *(1 if 'very concerned' about battery degradation of V2G; 0 otherwise)*	0.10	0.31
V2G Barrier – Data Privacy *(1 if 'neutral' to 'very concerned' about data privacy and security of V2G; 0 otherwise)*	0.70	0.46
V2G Barrier – Flexibility Loss *(1 if 'fairly concerned' or 'very concerned' about flexibility loss of V2G; 0 otherwise)*	0.15	0.35

5.5. *Overarching findings*

This section brings together results from the three separate models, highlighting key user characteristics that were found to significantly influence V2G preferences. Table 8 presents a summarized overview of these overarching findings, indicating general tendencies for specific user characteristics based on the direction of the parameter estimates. As discussed in Section 4.1.3, these tendencies are interpreted relative to the reference group for each user characteristic (e.g., lower versus higher income). Detailed model results for likelihood of participation, main drivers, and main barriers can be found in Tables 3, 5 and 7, respectively.

By consolidating findings across models, we gain nuanced insights into how specific user characteristics align with preferences, particularly where significant effects are observed across the different models. For instance, female respondents demonstrate a lower likelihood of participating in the first model, while the third model indicates that they tend to have flexibility loss as their primary concern. This points to a potential preference for preserving autonomy and control over vehicle usage, which may outweigh participation incentives. Similarly, respondents without children also show a lower likelihood of participation in the first model; the second model indicates they are less likely to prioritize financial drivers—focusing instead on environmental or grid-related motivations—while the third model shows that they tend to be most concerned about flexibility loss. For both groups, the perceived loss of flexibility appears to outweigh the benefits offered by incentives.

Notably, some indicator variables—such as age, education, income, household composition, car type, remote working, driving frequency—were slightly adjusted across models to enhance model fit, yet remained consistent enough to allow general observations. For instance, across the different models, we can infer that higher-educated individuals tend to be more likely to participate, with a higher probability that environmental reasons are their primary driver, while flexibility loss tends to be their main barrier. In contrast, lower-income respondents are generally less likely to participate; they tend to prioritize financial drivers, with data privacy and security more likely as their main barrier.

Overall, these consolidated findings reveal how user characteristics shape V2G preferences, providing deeper insights into participation likelihood and highlighting primary drivers and barriers influencing this tendency.

6. Policy implications

The survey responses indicate that, while financial motivations and flexibility concerns are the top priorities for most respondents, all other identified drivers (environmental and electricity grid) and barriers (battery degradation and data concerns) remain important. This highlights the need for a balanced policy approach that addresses each barrier while promoting all drivers to effectively support V2G adoption.

Alongside the general recommendations, we translate specific findings into targeted policy recommendations tailored to different user groups, based on patterns observed in Table 8. The detailed estimation results—covering participation likelihood, main drivers, and main barriers—are presented in Tables 3, 5 and 7, respectively.

First, targeted education and communication campaigns could increase participation by reinforcing engagement among those already inclined to participate (those most receptive) and encouraging hesitant groups, such as females and older individuals. Addressing key concerns specific to potential user groups—such as EV range anxiety and flexibility concerns among female car drivers, battery degradation among fossil fuel vehicle drivers, and data concerns among lower-educated and lower-income users—could help reshape V2G perceptions and improve participation rates. Furthermore, this study highlights that, alongside financial incentives, a significant portion of respondents highly value environmental and electricity grid reasons for V2G participation. Policymakers could leverage this by highlighting V2G's positive impact in these areas. Specifically, tailored messaging to resonate with user groups that prioritize specific values—for example highlighting the positive environmental impact towards urban dwellers, higher-educated

Table 5
Mixed logit model on the main drivers to participate in V2G (n = 518). Parameters defined for the following alternatives: financial [F], environmental [E] or electricity grid [G].

Variable description	Estimated parameter	t-statistic	Marginal effects		
			Financial [F]	Environmental [E]	Electricity grid [G]
Constant [E]	−2.26	−4.16			
Socio-demographic factors					
Random parameters *(standard deviation of parameter distribution)*					
Lower Income Indicator[a] [F] *(≤ €50.000/year)*	0.72 *(2.66)*	2.21 *(2.40)*	0.030	−0.015	−0.015
Fixed parameters					
Mature Age Indicator [F] *(≥ 65 years)*	−0.87	−2.28	−0.024	0.011	0.013
Higher Income Indicator [F] *(≥ €100.000/year)*	0.68	2.03	0.016	−0.009	−0.007
Higher Education Indicator [E] *(≥ bachelor of applied science)*	0.68	2.51	−0.034	0.066	−0.032
Household factors					
Fixed parameters					
Children Indicator [F] *(no children)*	−1.09	−3.63	−0.117	0.055	0.062
Household Composition Indicator [E] *(partner and children)*	0.71	2.45	−0.020	0.035	−0.015
Living Area Indicator [E] *(urban area)*	0.41	1.71	−0.014	0.029	−0.015
Low Electricity Bill Indicator [E] *(≤ €100/month)*	0.69	2.72	−0.031	0.062	−0.031
Household Size Indicator [G] *(one person)*	−1.19	−3.50	0.011	0.016	−0.027
Car use factors					
Fixed parameters					
Main Mode Indicator – Car [F]	0.99	3.84	0.106	−0.049	−0.057
Car Access Indicator – Car Sharing [F]	−0.78	−1.88	−0.013	0.006	0.006
Car Access Indicator – Car Owner [E]	0.69	1.86	−0.046	0.093	−0.046
Vehicle Type Indicator – Electric Vehicle [E]	0.65	1.91	−0.008	0.016	−0.008
Remote Working Indicator [G] *(never remote working)*	−0.59	−2.30	0.023	0.023	−0.046
Car Use Type – Commute [G] *(≥ 5 days/week)*	0.51	1.92	−0.013	−0.010	0.023
Attitude and preference factors					
Fixed parameters					
Car Attachment Indicator [F] *(not attached)*	1.24	2.28	0.012	−0.005	−0.006
V2G Familiarity Indicator [F] *(never heard of it)*	0.47	1.79	0.049	−0.024	−0.026
Smart Home Technology Interest Indicator [F] *(interested)*	−0.42	−1.67	−0.043	0.022	0.021
EV Concern Indicator – Initial Costs [F]	0.53	2.10	0.046	−0.022	−0.023
V2G Barrier – Battery Degradation [F] *(very concerned)*	1.05	2.58	0.017	−0.009	−0.008
V2G Barrier – Flexibility Loss [E] *(concerned)*	−0.53	−1.51	0.005	−0.011	0.006
Technology Enthusiasm Indicator [E] *(enthusiastic)*	0.48	1.91	−0.025	0.049	−0.025
V2G Barrier – Data Privacy [G] *(concerned)*	0.40	1.68	−0.023	−0.022	0.045
Model Fit					
LL *(start)*	−569.08				
LL *(final)*	−485.98				
McFadden Pseudo R-squared	0.15				
AIC	1022.0				
Halton draws	1000				
Number of parameters	25				
Number of observations	518				

[a] For a full description of the indicator variable, refer to the corresponding indicator variable in Table 4.

individuals, and households with children—could further enhance engagement. However, while targeted campaigns may be a practical way to engage different user groups, the ethical implications warrant careful consideration. Policymakers should prioritize transparency, inclusivity, and user autonomy to ensure these efforts genuinely serve the public interest.

Second, policymakers should continue to incentivize EV adoption and shared mobility practices, as our results indicate that current EV drivers and car sharers are more inclined to participate in V2G. Additionally, our findings suggest that V2G-related concerns reflect general EV-related concerns; for example, concerns over the high initial costs of EVs leads to a prioritization of financial drivers for V2G participation. Moreover, experience with EVs appears to alleviate previously held EV-related concerns, such as range anxiety (as also reported by Bühler et al., 2014; Gschwendtner and Krauss, 2022; Rauh et al., 2015), which could, in turn, reduce V2G-related concerns. For instance, if range anxiety decreases, concerns about loss of flexibility or battery degradation may also diminish. Complementarily, promoting V2G with appropriate incentives could help persuade hesitant fossil-fuel car drivers to adopt a V2G-enabled EV. However, it is worth noting that, as current EV ownership primarily includes early adopters[21], these preferences may evolve as adoption expands to a broader and more diverse user base.

Third, convenient charging infrastructure could significantly influence V2G engagement, as evidenced by the increased likelihood of participation among those with private parking access. For instance, providing more home charging options might increase participation and alleviate flexibility concerns. Additionally, workplace charging infrastructure is likely to increase participation, considering the influence of factors relating to the employment status and regular commuting patterns. This is an important leverage point, as respondents who drive frequently, particularly for commuting, are found more likely to participate in V2G.[22] However, expanding charging infrastructure involves trade-offs, particularly relating to costs and the grid. Increased

[21] Early EV adopters tend to have high incomes, education, and environmental concerns (Rogers et al., 2014; Carley et al., 2013; Plötz et al., 2014; Hardman et al., 2016).

[22] This aligns with previous studies indicating that charging infrastructure—especially fast charging—could be a crucial leverage point to increase V2G participation (Huang et al., 2021; Kajanova et al., 2021).

Table 6
Summary statistics of variables included in the final model estimation on the main barriers relating to V2G participation (n = 434).

Variable description	Mean	Standard deviation
Socio-demographic factors		
Gender Indicator *(1 if identifies as female; 0 otherwise)*	0.48	0.50
Lower Education Indicator *(1 if completed high school or lower; 0 otherwise)*	0.18	0.38
Higher Education Indicator *(1 if completed a master's degree or higher; 0 otherwise)*	0.23	0.42
Lower Income Indicator *(1 if household annual income before taxes is €40,000 or less; 0 otherwise)*	0.35	0.48
Working Situation Indicator *(1 if works part-time (up to 32 h) or full-time (more than 32 h); 0 otherwise)*	0.63	0.48
Household factors		
Children Indicator *(1 if does not have children under the age of 18 in the household; 0 otherwise)*	0.69	0.46
Household Composition Indicator *(1 if lives with a partner, either with or without children; 0 otherwise)*	0.70	0.46
Household Size Indicator *(1 if lives in a one-person household; 0 otherwise)*	0.20	0.40
Car use factors		
Vehicle Type Indicator – Electric Vehicle *(1 if mainly drives an electric vehicle; 0 otherwise)*	0.13	0.33
Car Access Amount Indicator *(1 if household has regular access to only one car; 0 otherwise)*	0.68	0.47
Car Access Indicator – Not Car Owner *(1 if does not own their car(s); 0 otherwise)*	0.15	0.35
Car Access Indicator – Business Lease Indicator *(1 if business leases their car; 0 otherwise)*	0.12	0.32
Car Access Indicator – Car Sharing *(1 if involved in car sharing; 0 otherwise)*	0.88	0.32
Commute Indicator *(1 if does not have a daily commute; 0 otherwise)*	0.27	0.44
Driving Frequency Indicator *(1 if drives 11 days per year or less; 0 otherwise)*	0.04	0.21
Attitude and preference factors		
V2G Familiarity Indicator *(1 if 'neutral' to 'very familiar' with V2G; 0 otherwise)*	0.19	0.39
Environmental Importance Indicator *(1 if considers environmental sustainability 'fairly important' or 'very important' in decision-making; 0 otherwise)*	0.62	0.48
Smart Home Technology Interest Indicator *(1 if 'not that interested' or 'not interested at all' in using smart home technologies; 0 otherwise)*	0.14	0.34
V2G Driver Indicator – Financial *(1 if considers financial reasons 'very important' for participating in V2G; 0 otherwise)*	0.21	0.41
V2G Driver Indicator – Environmental *(1 if considers environmental reasons 'not important at all' for participating in V2G; 0 otherwise)*	0.07	0.25

access may enhance convenience and participation, but higher infrastructure costs—borne by individuals or society—and potential grid congestion from increased charging demand must be carefully managed to ensure long-term feasibility.

Fourth, income-based incentives should be strategically implemented to actively engage diverse income groups. Tailoring financial incentives—such as direct compensation (fixed or variable), subsidies, or discounted rates—can effectively cater to the preferences of both lower-income individuals (€50,000 or less annually) and high-income earners (€100,000 or more annually), as financial motivations are the primary driver for V2G participation across both groups. However, such a tailored approach may introduce administrative complexities, risk inefficient resource allocation, and potentially overlook middle-income groups. Additionally, excessive reliance on subsidies could undermine long-term market sustainability and distort consumer behavior. Hence, careful policy design is essential to balance equity, cost-effectiveness, and grid stability.

Fifth, we advocate for implementing a regulatory framework that prioritizes both technological development and user protection, particularly focused on addressing the main V2G barriers. Technological advancements can play a crucial role in reducing these barriers; for example, enhanced predictive algorithms can enhance user flexibility, advanced energy management systems can limit battery degradation, and improved cybersecurity protocols can alleviate data security risks. Additionally, the regulatory framework can reduce user uncertainties; for example, flexible participation models can reduce flexibility concerns, battery health guarantees can alleviate worries about battery degradation, and transparent data practices can ease data concerns.

Finally, as V2G is still in its early stages with limited commercial applications, continuous monitoring and policy adjustments, guided by public engagement, are imperative to remain responsive to evolving societal attitudes and technological advancements. This approach ensures that V2G initiatives are aligned with the diverse preferences of various user demographics.

7. Conclusions

This study set out to answer the following research question: "*What is the likelihood of potential users to participate in a V2G program, and how important are various drivers and barriers for their willingness to participate?*" To answer this question, we administered a stated preference survey in the Netherlands that contained approximately forty-five stated intentions and user characteristics questions, including those about the likelihood of participating in V2G, level of importance for the main drivers, and level of concern for the main barriers. A total of 1018 representative participants completed the survey. The responses were analyzed with three separate statistical models that account for unobserved heterogeneity. The first part of the research question on likelihood of participation was analyzed using a random parameters ordered probit model. To address the second part of the question, two separate random parameters multinomial logit models (mixed logit models) were estimated: one focused on drivers and the other on barriers.

Regarding the likelihood of V2G participation, we found a majority expressing to be likely to participate (42%), with a minority unlikely (26%), and about a third remaining neutral (32%). For the main drivers, we found a majority primarily driven by financial reasons (49%), with the remaining respondents nearly evenly divided between environmental (25%) and electricity grid drivers (26%). For the main barriers we found a majority expressing loss of flexibility as their main barrier (55%), followed by battery degradation (27%), and data privacy and security (18%). Additionally, the model estimations reveal how various 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 factors (e.g., attitudes towards cars, environmental awareness)—influence these preferences. Combining model results provided valuable insights into participation likelihood across user groups, along with the main drivers and barriers shaping these tendencies.

While this study provides valuable insights into V2G preferences, some limitations should be considered. First, as the research relies on stated preference survey data, responses may be subject to hypothetical bias, where the participants' expressed intentions may not fully reflect their real-world behavior. Second, although the sample captures a broad range of user characteristics, it is specific to the Netherlands, which may limit transferability to other countries. Third, while the statistical models offer detailed insights, they cannot capture all contextual

Table 7
Mixed logit model on the main barriers relating to V2G participation (n = 434). Parameters defined for the following alternatives: battery degradation [B], data privacy and security [D] or loss of flexibility [L].

Variable description	Estimated parameter	t-statistic	Marginal effects		
			Battery degradation [B]	Data privacy and security [D]	Loss of flexibility [L]
Constant [D]	−2.25	−1.95			
Socio-demographic factors					
Random parameters *(standard deviation of parameter distribution)*					
Working Situation Indicator[a] [B] *(employed part- or full-time)*	−7.50 *(13.01)*	−1.81 *(2.00)*	0.009	−0.0001	−0.009
Gender Indicator [L] *(female)*	2.23 *(5.04)*	1.60 *(1.79)*	−0.019	−0.007	0.026
Fixed parameters					
Lower Education Indicator [D] *(≤ high school diploma)*	1.80	1.97	−0.007	0.016	−0.009
Lower Income Indicator [D] *(≤ €40.000/year)*	1.99	2.10	−0.012	0.026	−0.014
Higher Education Indicator [L] *(≥ master's degree)*	2.48	1.99	−0.016	−0.007	0.023
Household factors					
Fixed parameters					
Household Composition Indicator [B] *(with partner)*	4.07	1.93	0.115	−0.036	−0.080
Household Size Indicator [D] *(one person)*	−5.20	−2.22	0.009	−0.023	0.014
Children Indicator [L] *(no children)*	1.85	1.96	−0.033	−0.023	0.056
Car use factors					
Random parameters *(standard deviation of parameter distribution)*					
Car Access Amount Indicator [L] *(one car)*	−2.30 *(6.40)*	−1.81 *(2.27)*	0.031	0.025	−0.056
Fixed parameters					
Vehicle Type Indicator – Electric Vehicle [B]	−6.69	−2.39	−0.019	0.005	0.014
Car Access Indicator – Car Sharing [B]	−4.80	2.05	−0.161	0.050	0.112
Car Access Indicator – Business Lease Indicator [D]	4.61	2.19	−0.006	0.021	−0.015
Driving Frequency Indicator [D] *(≤ 11 days/year)*	3.62	2.12	−0.002	0.007	−0.005
Commute Indicator [L] *(no daily commute)*	−2.31	−2.05	0.025	0.009	−0.034
Car Access Indicator – Not Car Owner [L]	2.92	1.73	−0.008	−0.009	0.017
Attitude and preference variables					
Random parameters (standard deviation of parameter distribution)					
Environmental Importance Indicator [D] *(important)*	−11.50 *(13.82)*	−1.33 *(1.57)*	−0.005	0.017	−0.012
Fixed parameters					
V2G Driver Indicator – Financial [B] *(very important)*	3.82	3.13	0.036	−0.014	−0.022
V2G Driver Indicator – Environmental [B] *(not important at all)*	2.58	1.82	0.009	−0.004	−0.005
V2G Familiarity Indicator [B] *(familiar)*	5.00	2.27	0.034	−0.008	−0.026
Smart Home Tech Interest Indicator [D] *(not interested)*	2.46	2.34	−0.009	0.018	−0.009
Model fit					
LL *(start)*	−476.80				
LL *(final)*	−373.64				
McFadden pseudo R-squared	0.22				
AIC	797.3				
Halton draws	1000				
Number of parameters	25				
Number of observations	434				

[a] For a full description of the indicator variable, refer to the corresponding indicator variable in Table 6.

factors—such as real-time electricity price fluctuations or evolving user preferences—that may influence participation dynamics over time. Future research could build on the findings from this work by integrating user behavior and preferences into simulation models, such as agent-based models, to explore dynamic participation patterns.

We also provide policy recommendations to improve consumer acceptance. First, we recommend targeted education and communication campaigns aimed at decreasing barriers and emphasizing the drivers. Second, we recommend continued incentivization of EV adoption and shared mobility practices, as these measures are likely to increase V2G acceptance. Third, we recommend prioritization of convenient charging infrastructure. This includes focusing on home and workplace charging solutions to facilitate seamless integration of V2G systems. Fourth, we recommend income-based incentives tailored to different income groups. These incentives could take the form of direct compensation, subsidies, or discount rates, reflecting the diverse preferences and circumstances of potential V2G users. Fifth, we recommend fostering technical development and ensuring robust user protection measures, aimed at alleviating the main V2G barriers. Lastly, given the nascent stage of V2G technology, we recommend continuous monitoring and policy adjustments to remain aligned with evolving user preferences and technological advancements.

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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,

Table 8
Overarching findings across all three models. This table summarizes findings on the likelihood of participation and main influencing factors—drivers (financial [F], environmental [E], or electricity grid [G]) and barriers (battery degradation [B], data concerns [D], or flexibility loss [L]). An upwards arrow (↑) signifies higher likelihood, while a downwards arrow (↓) indicates a lower likelihood compared to the reference. For example, '↑ [E]' for those higher educated suggests an increased likelihood of prioritizing environmental drivers compared to those lower educated.[b]

User characteristics	Indicator variables	Participation likelihood	Main driver	Main barrier
Socio-demographic factors	Gender – Female	↓	–	↑ [L][a]
	Age – Older *(≥ 62 years)*	↓[a]	–	–
	Age – Older *(≥ 65 years)*	–	↓ [F]	–
	Age – Younger *(≤ 25 years)*	↓	–	–
	Education – Higher *(≥ bachelor of applied science)*	↑	↑ [E]	–
	Education – Higher *(≥ master's degree)*	–	–	↑ [L]
	Education – Lower *(≤ high school diploma)*	–	–	↑ [D]
	Income – Higher *(≥ €100.000/year)*	↑	↑ [F]	–
	Income – Lower *(≤ €60.000/year)*	↓[a]	–	–
	Income – Lower *(≤ €50.000/year)*	–	↑ [F][a]	–
	Income – Lower *(≤ €40.000/year)*	–	–	↑ [D]
	Employed – Part- or full-time	–	–	↓ [B][a]
Household factors	Household composition – Partner, with or without children	–	–	↑ [B]
	Household composition – Partner, with children	–	↑ [E]	
	Household size – One-person	–	↓ [G]	↓ [D]
	Children – No children	↓	↓ [F]	↑ [L]
	House type – Apartment	↓	–	–
	Living area – Urban	↑	↑ [E]	–
	Home private parking access	↑	–	–
	Home renewable energy use	↑	–	–
	Electricity bill – Lower *(≤ €100/month)*	–	↑ [E]	–
Car use factors	Car type – Electric Vehicle	–	↑ [E]	↓ [B]
	Car type – Fossil Fuel Vehicle	↓	–	–
	Main Transport Mode – Car	–	↑ [F]	–
	Car access amount – One	–	–	↓ [L][a]
	Car access type – Owner	–	↑ [E]	–
	Car access type – Non-owner	–	–	↑ [L]
	Car access type – Business Lease	–	–	↑ [D]
	Car access type – Car Sharing	↑	↓ [F]	↓ [B]
	Car use type – Commute *(≥ 5 days/week)*	↑	↑ [G]	–
	Car use type – Leisure *(≥ 5 days/week)*	↑[a]	–	–
	Remote working – Never	–	↓ [G]	–
	Remote working – Almost never *(≤ 1 day/week)*	↓	–	–
	Commute – Never *(no daily commute)*	↓	–	↓ [L]
	Driving Frequency – Almost never *(≤ 11 days/year)*	–	–	↑ [D]
	Driving Frequency – Infrequent *(≤ 3 days/month)*	↓	–	–
	Long journey frequency – Frequent *(≥ 11 days/month)*	↓	–	–
Attitude and preference factors	V2G Familiarity – Never heard of it	–	↑ [F]	–
	V2G Familiarity – Familiar	–	–	↑ [B]
	Car attachment indicator – Not attached	↓	↑ [F]	–
	Environmental importance indicator – Not important	↓[a]	–	–
	Environmental importance indicator – Important	–	–	↓ [D][a]
	Smart home tech interest – Interested	–	↓ [F]	–
	Smart home tech interest – Not interested	–	–	↑ [D]
	Technology Enthusiasm – Enthusiastic	–	↑ [E]	–
	EV concerns – Driving Range	↓[a]	–	–
	EV concerns – Initial Costs	–	↑ [F]	–
	V2G Drivers – Financial *(very important)*	–	–	↑ [B]
	V2G Drivers – Environmental *(not important at all)*	–	–	↑ [B]
	V2G Barriers – Battery Degradation *(very concerned)*	–	↑ [F]	–
	V2G Barriers – Data Concerns *(concerned)*	–	↑ [G]	–
	V2G Barriers – Loss of Flexibility *(concerned)*	–	↓ [E]	–

[a] Indicates significant heterogeneity within the group (random parameter).
[b] Note that some indicator variables differ slightly across models (e.g., ≤ €60,000/year vs. ≤ €50,000/year for *lower income*, or ≥≥ 62 years vs. ≥ 65 years for *older age*). These variations were made to maximize model fit and statistical significance for each separate model.

Methodology, Data curation, Conceptualization. **Émile J.L. Chappin:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix A. : Supplementary Literature Review

Table A.1
Summary of key findings from V2G choice modeling studies.

Study	Research Design	Methods	Key Outcomes	Recommendations
Parsons et al. (2014)	Stated-preference survey (U.S., N = 3029) comparing V2G-EVs with gasoline vehicles based on V2G contract attributes: plug-in time, guaranteed driving range, and annual cash-back payments.	Latent class model.	- High perceived inconvenience due to flexibility loss (plug-in time & minimum guaranteed range). - Consumers heavily discounted uncertain V2G payments, requiring compensation ($2368–$8622) far above feasible market rates (~ $2900), suggesting limited competitiveness of V2G EVs.	Flexible contract models (e.g., pay-as-you-go or upfront payments) to improve consumer appeal.
Hidrue and Parsons (2015)	Follow-up study of Parsons et al. (2014) using same survey data to assess near-term market feasibility of V2G-EVs under different battery cost scenarios.	Demand estimation & willingness to pay analysis.	- Willingness to pay was consistently lower than production costs, even under optimistic scenarios. - Concerns over range anxiety, restrictive contracts (e.g., long plug-in hours), and battery costs reduced interest. - High implicit discount rates (53%) made annual cash payments unattractive.	Less restrictive contracts and upfront subsidies instead of annual payments.
Geske and Schumann (2018)	Stated-preference survey (Germany, N = 611, incl. 14 EV drivers) analyzing V2G contract attributes: minimum range requirements, plug-in time restrictions, and financial incentives.	Ordinal regression & latent class model.	- High general interest in V2G, with an average willingness score of 4.7 out of 7, driven by cost savings and support for renewable energy. - Main concerns: battery degradation, trip unpredictability, uncontrolled access, and insufficient charge levels. - Range anxiety and minimum range constraints were most influential. - Remuneration (monthly or one-time payments) was less effective than expected.	If main concerns (i.e., range anxiety) are addressed, high participation rates are possible even without financial incentives.
Kubli et al. (2018)	Choice-based conjoint experiments (Switzerland, N = 902) analyzing prosumer willingness to provide flexibility through V2G, solar PV storage, and heat pumps. V2G was assessed based on participation, battery discharge cycles, and guaranteed charging levels.	Hierarchical Bayes estimation.	- Higher willingness for V2G than heat pumps, but participation dropped sharply if guaranteed charge fell below 60%. - Key drivers: monetary compensation & transparency.	Tailored business models and policies aligning V2G incentives with user needs. Importance of trust, automation, and dynamic pricing.
Noel et al. (2019c)	Stated choice experiment (five Nordic countries, N = 4762) evaluating willingness to pay for V2G as a general EV attribute without restrictive contract terms, such as plug-in time.[a]	Mixed logit model.	- High willingness to pay for V2G in Norway (€5200) and Finland (€4000), making it a cost-effective way to boost EV adoption. - Low willingness to pay in Denmark, Sweden, and Iceland, due to low awareness, skepticism about revenues, battery degradation concern, and perceived inconvenience with trip planning.	Consumer education and visible policy support to increase awareness and improve adoption.
Zonneveld (2019)	Stated-preference survey (Netherlands, N = 96) comparing price- and volume-based V2G contracts, focusing on five attributes: Remuneration, Guaranteed range, number of discharging cycles, contract duration, and plug-in time.	Multinomial logit model.	- Most influential factors: remuneration, guaranteed range, discharging cycles. - High-income users showed less interest. - Range anxiety was higher among female participants.	Dynamic V2G pricing models and contract customization to align incentives with grid flexibility needs.
Huang et al. (2021)	Stated choice experiment (Netherlands, N = 148) testing EV drivers' willingness to participate in V2G under current vs. fast-charging conditions. Analyzed contract attributes were remuneration, plug-in time, guaranteed minimum battery level, discharging cycles, and contract duration.	Multinomial logit model.	- Low V2G interest with slow charging, but interest increased significantly with fast charging. - Most influential attribute: discharging cycles (i.e., battery degradation concerns). - Guaranteed minimum battery level was also important but became less critical with fast charging. - Participants also strongly disliked long plug-in times, while higher remuneration increased participation.	Promotion of fast-charging infrastructure and flexible plug-in contracts can enhance adoption.
Kajanova et al. (2021)	Stated-preference survey (Slovakia, N = 289) analyzing decision-making at charging stations. Participants chose between slow charging, fast charging, and discharging (V2G). Key contract attributes: charging cost, state of charge, probability of needing extra range, energy sold in V2G, and monetary rewards per kWh.	Multinomial logit model.	- V2G was unpopular unless high rewards were offered. - Higher state of charge increased V2G participation, while greater uncertainty about travel needs reduced it. - Strong preference for monetary incentives & selling larger energy amounts for higher rewards.	User segmentation for better adoption strategies based on socio-demographics and travel needs.

[a] The authors expect that V2G would rely on aggregated sources and forecasting rather than restrictive individual contracts.

Appendix B. : Summary Statistics for Used Samples

Table B.1
Comparison of summary statistics for the full sample and subsamples.

		Full Sample (n = 1018)	Drivers Subsample (n = 518)	Barriers Subsample (n = 434)
Variable	Categories	Percentage of respondents	Percentage of respondents	Percentage of respondents
Age	18–24	4%	5%	6%
	25–30	9%	10%	11%
	31–40	17%	19%	17%
	41–50	17%	16%	17%
	51–60	19%	19%	18%
	61–65	10%	11%	12%
	>65	24%	20%	19%
Gender	Male	53%	54%	52%
	Female	47%	46%	48%
	Other	0%	0%	0%
Education	Primary school	1%	1%	1%
	VMBO or MAVO	15%	15%	10%
	HAVO or VWO	7%	7%	7%
	Secondary vocational education	23%	21%	23%
	Bachelor of applied science	28%	28%	30%
	Bachelor of science	6%	6%	6%
	Master of science or higher	20%	22%	23%
Vehicle type	Full Electric	11%	13%	13%
	Hybrid	18%	17%	16%
	Fossil	71%	70%	71%
V2G Familiarity	Never heard of it before	63%	66%	62%
	Heard of it, but not well known	19%	17%	19%
	Somewhat familiar	11%	8%	10%
	Fairly familiar	3%	5%	5%
	Very familiar	4%	4%	4%

Data availability

Data will be made available on request.

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