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LETTER

Measuring electric vehicle owners' willingness to participate in smart charging programs

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Supplementary material for this article is available online

Abstract

As power systems transition to renewable energy, integrating battery electric vehicles (BEVs) into grid operations presents new opportunities and challenges for managing electricity demand and the associated environmental impacts from BEV charging. This study examines two grid-integration strategies: supplier-managed charging (SMC), which gives utilities control over charging timing, and vehicle-to-grid (V2G), which transforms BEVs into distributed energy storage resources. Using a discrete choice experiment with 1,356 current BEV owners, we quantify how program attributes influence enrollment decisions. Using multinomial logit models, results suggest that SMC participants predominantly value operational flexibility and recurring payments while V2G participants prefer monetary incentives, indicating a willingness to provide grid services for compensation. Through simulation analysis, we identify program 'attribute equivalencies' that quantify changes needed in attributes to achieve equivalent enrollment levels. These findings can be used in the design of market mechanisms and policy frameworks that accelerate BEV integration into future energy systems.

Glossary

BEV	Battery electric vehicle
CV	Conventional vehicle, referring to non-hybrid gasoline-powered internal combustion engine vehicles
GHGs	Greenhouse gases
MLE	Maximum likelihood estimation
MNL	Multinomial logit
SMC	Supplier-managed charging
UMC	User-managed charging
V2G	Vehicle-to-grid

1. Introduction

The integration of BEVs into power systems represents both a challenge and an opportunity for grid operators working to decarbonize energy systems (Sachs *et al* 2020). BEVs represent a key strategy for transportation sector decarbonization, with the potential to significantly reduce vehicle life cycle GHGs and criteria air pollutant emissions when adopted in concert with cleaner electricity (Elgowainy *et al* 2018, Jenkins *et al* 2021, Shukla *et al* 2022). However, these emissions reductions depend not only on the emissions intensity of electricity sources (McLaren *et al* 2016) but also on the timing of vehicle charging. Uncontrolled BEV charging often coincides with peak electricity demand and typically occurs when renewable or low-carbon resources are limited (Zhang *et al* 2011, 2020), potentially increasing grid stress, infrastructure costs, and GHG emissions while constraining the emissions reduction potential of BEVs (Tarroja et al 2015).

A promising solution is to implement grid-interactive charging strategies (often referred to broadly as 'smart charging' strategies), which can transform BEVs from passive loads into flexible grid resources that support renewable energy integration and enhance power system operation (Tarroja et al 2015, Forrest et al 2016, Xu et al 2025). Two key approaches have emerged: SMC, which enables utilities to optimize charging timing and duration while ensuring batteries reach desired charge levels by predefined times (Dean and Kockelman 2024b), and V2G, which allows BEVs to provide bidirectional power flow as distributed energy storage resources, providing additional grid flexibility and potentially enabling more significant emission reductions compared to SMC alone (Tarroja et al 2016, Xu et al 2025). Both strategies have the potential for economic and environmental benefits through improved grid efficiency and renewable energy integration (Mets et al 2012, Tarroja et al 2015, Tarroja and Hittinger 2021).

The success of these grid-integration strategies fundamentally depends on BEV owners' willingness to participate in smart charging programs. Previous research suggests that most owners are reluctant to enroll without adequate incentives, citing concerns about operational limitations and insufficient compensation (Bailey and Axsen 2015, Sovacool et al 2018). Several studies have investigated consumer willingness to participate under different conditions. A recent analysis by Wong et al (2023) examined how incentive structures affect smart charging program acceptance using a discrete choice experiment, revealing that while monetary incentives are important, there are diminishing returns to continued payment increases. Another discrete choice experiment by Philip and Whitehead (2024) in Australia found that guaranteed driving range significantly influences participation willingness. Research on Dutch BEV owners by Huang et al (2021) showed that V2G participation increases when rapid recharging is available. These survey findings align with real-world evidence—a study by Bailey et al (2023) found that once financial incentives were removed from an SMC program, participants reverted to their original charging behavior. Similarly, Meyer et al (2022) found that behavioral educational communications layered on top of time-of-use rebate programs can enhance the effectiveness of price signals, achieving an approximate 8% reduction in on-peak charging behavior through targeted messaging and social norming strategies.

However, V2G also increases battery cycling frequency, which could accelerate battery degradation (Ahmadian et al 2018) and is a known concern among BEV owners (Dean and Kockelman 2024a). Effective programs must be designed with such concerns in mind, offering incentives to encourage participation such as monetary compensation and other features like guaranteed minimum battery charge levels (Huang et al 2021).

One important limitation of previous studies is their reliance on samples drawn primarily from the general car-owning public rather than actual BEV owners. This is problematic because charging experience is crucial for making informed choices about charging preferences (Neaimeh et al 2025). The BEV ownership rate among participants in the Wong et al (2023) study was 19% ($N = 151$ BEV owners), and in the Philip and Whitehead (2024) study it was just 1.28% (13 BEV owners), suggesting limited experience charging and driving a BEV. While the study by Huang et al (2021) included 99% BEV drivers, their total sample was only 157 respondents. Most studies that examine people's willingness to participate in these programs have primarily sampled from combustion vehicle owners who lack direct experience with BEV charging and who may have different preferences from actual BEV owners Parsons et al (2014), Kubli (2022), Lavieri and de Oliveira (2023), Wong et al (2023).

In this study, we focus exclusively on understanding the preferences of current BEV owners in the U.S., recognizing that smart charging programs must balance utility needs for demand-side flexibility with consumer preferences to achieve meaningful participation levels. We aim to quantify how different program attributes align with both grid integration and BEV owner objectives. We address two research questions: 1) how do changes in individual smart charging program attributes influence the willingness of BEV owners to opt into SMC and V2G programs, and 2) under what conditions will BEV owners be more willing to provide grid services through these programs?

Our study addresses these limitations by focusing exclusively on current BEV owners with a larger sample size ($N = 1356$) recruited through targeted survey methods. Using a discrete choice experiment, we quantify attribute trade-offs and identify program designs that could enable adoption of SMC and V2G programs. Our analyses provide utilities with practical guidance for developing smart charging programs that balance system optimization needs with consumer preferences, ultimately supporting the integration of BEVs into energy systems. The results illustrate which smart charging elements are most valuable to drivers and can be used to estimate the costs of policies or programs that seek to attract smart charging participants. The findings bridge an important gap between the technical potential of smart charging programs and the market mechanisms needed to attract consumer interest.

2. Method

We designed and fielded a nationwide discrete choice survey experiment online to quantify how different smart charging attributes affect BEV owners' willingness to participate in SMC and V2G programs. This approach presents respondents with varying choice scenarios to quantify how people make trade-offs between different alternatives due to differences in attributes. By observing choices across respondents and varying attributes across choice tasks, we can statistically estimate the relative importance and value that people place on each attribute—in this case, specific SMC and V2G program features such as enrollment incentives, monthly payments, or battery charge thresholds.

To ensure we sampled current BEV owners, we began the survey with a screener section where respondents selected their current vehicle make, model, and model year from a drop-down list of all possible vehicles in the last 30 years. Respondents were only allowed to continue if they selected a BEV model. We are confident that respondents were true BEV owners for several reasons: BEVs represented just 4.4% of model options (77 out of 1748 models), making random selection unlikely; there was no prior indication that the study was about BEVs; and prior research shows most Americans struggle to accurately name even one BEV model (Kurani 2018), suggesting few would know which models were BEVs unless they owned one.

The conjoint choice questions used randomized sets of choice tasks generated using the `cbcTools` R package (Helveston 2024). Rather than use a 'D-optimal' design, which selects choice sets to efficiently identify main effects (Goos and Jones 2011, Eendebak and Schoen 2017, Walker *et al* 2018), a purely random design was chosen to enable identification of potential interaction effects and provide greater coverage across all combinations of attribute levels. Respondents were asked six consecutive choice questions for SMC programs, then six additional choice questions for V2G programs. Each choice question included two smart charging options and a 'not interested' option, consistent with the voluntary nature of real smart charging programs.

We selected 5 attributes each for SMC and V2G programs based on reviewing prior literature, existing utility programs, and interviews with utility program managers. For SMC programs, attributes included: *enrollment cash* (one-time payment), *monthly cash* (monthly payment), *override allowance* (number of times per month driver can override and charge immediately), *minimum threshold* (BEV will always be immediately charged up to this point), and *guaranteed threshold* (guaranteed BEV charge at end of charging period). For V2G programs, attributes included: *enrollment cash*, *occurrence cash* (payment per V2G event), *monthly occurrence* (maximum number of V2G discharges per month), *lower threshold* (BEV will never be discharged below this state of charge), and *guaranteed threshold*. A complete list of attribute levels are shown in tables 1 and 2, and figures 1 and 2 show example choice questions for the SMC and V2G questions.

The survey was fielded in two stages from March to November 2024. First, we implemented targeted advertisements on Meta's Facebook and Instagram platforms, following ad-based survey recruitment guidelines by Kühne and Zindel (2020). We leveraged Meta's targeting capabilities to focus on likely BEV owners based on sustainability-related and BEV-specific interests, yielding 803 responses. Second, we recruited respondents through Dynata, a market research company, paying \$10 per valid respondent and targeting previously identified BEV owners to reach underrepresented demographic groups, yielding 553 responses. The total sample included 1356 respondents who completed SMC choice questions, with 682 completing the optional V2G section. Our sample demographics match other studies targeting U.S. BEV owners, which tend to be wealthier, older, and more male than the general population (Chakraborty *et al* 2022). Summaries of the complete demographic information is provided in the supplementary information.

Consumer choice was modeled using a random utility framework, which assumes that respondents chose the alternative with higher utility in each choice question (Louviere *et al* 2000). Random utility is calculated as the sum of weighted attributes and a random error term:

$$u_j = v_j + \epsilon_j = \beta'\mathbf{x} + \epsilon_j \tag{1}$$

where β is a vector of weights to be estimated, $\mathbf{x}$ is a matrix of attributes, and ϵ_j is an error term that follows a Type 1 extreme value distribution. Given this form, the probability of choosing alternative j from a set of J alternatives follows the logit probability function:

$$P_j = \frac{e^{v_j}}{\sum_{k=1}^{J} e^{v_k}}. \tag{2}$$

The utility model for the SMC program is:

$$\begin{aligned} u_j = {} & \beta_1 x_j^{\text{enroll}}\_\text{cash} + \beta_2 x_j^{\text{monthly}}\_\text{cash} \\ & + \beta_3 \delta_j^{\text{override}}\_\text{allowed} * \beta_4 x_j^{\text{num}}\_\text{overrides} \\ & + \beta_5 x_j^{\text{min}}\_\text{threshold} + \beta_6 x_j^{\text{guaranteed}}\_\text{threshold} \\ & + \beta_7 \delta_j^{\text{no}}\_\text{choice} + \epsilon_j. \end{aligned} \tag{3}$$

Table 1. SMC program attributes.

No.	Attribute	Range	Explanation
1	Enroll. cash	\$50, \$100, \$200,\$300	One-time payment on enrollment
2	Monthly cash	\$2, \$5,\$10,\$15,\$20	Recurring monthly payment
3	Override allow.	0, 1, 3, 5	Monthly free overrides to normal
4	Min. threshold	20%, 30%, 40%	SMC not triggered below this
5	Guar. threshold	60%, 70%, 80%	Guaranteed range by morning

Attributes and ranges based on prior surveys (Wong *et al* 2023, Dean and Kockelman 2024b) and utility company input.

Table 2. V2G program attributes.

No.	Attribute	Range	Explanation
1	Enroll. cash	\$50,\$100,\$200,\$300	One-time payment on enrollment
2	Occur. cash	\$2,\$5,\$10,\$15,\$20	Earning per V2G occurrence
3	Monthly occur.	1, 2, 3, 4	Monthly V2G occurrences
4	Lower threshold	20%, 30%, 40%	Min. battery level during V2G
5	Guar. threshold	60%, 70%, 80%	Battery recharged to this level

See descriptions in table 1.

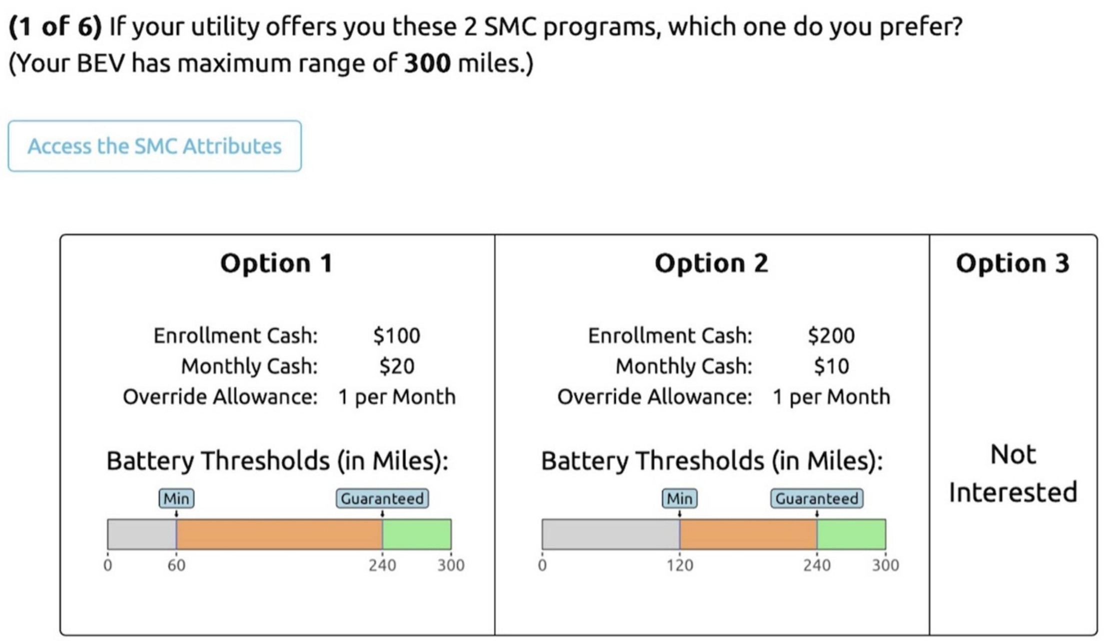

Figure 1. Sample SMC conjoint question. Each respondent was asked 6 choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

Note that we modeled the *override allowance* attribute as two different coefficients: a discrete variable for whether or not *any* override allowance was allowed ($\delta_j^{\text{override}}$_allowed) interacted with a continuous variable for the total number of overrides allowed(x_j^{num}_overrides). We made this choice because we expected a non-linearity in utility between having the ability to override at all and the number of overrides per month, which should exhibit diminishing returns.

The utility model for the V2G program is:

$$u_j = \beta_1 x_j^{\text{enroll}}\_\text{cash} + \beta_2 x_j^{\text{occur}}\_\text{cash} + \beta_3 x_j^{\text{num}}\_\text{occurrences} + \beta_4 x_j^{\text{lower}}\_\text{threshold} + \beta_5 x_j^{\text{guaranteed}}\_\text{threshold} + \beta_6 \delta_j^{\text{no}}\_\text{choice} + \epsilon_j. \quad (4)$$

We estimated mixed logit (MXL) models for each smart charging program via MLE using the

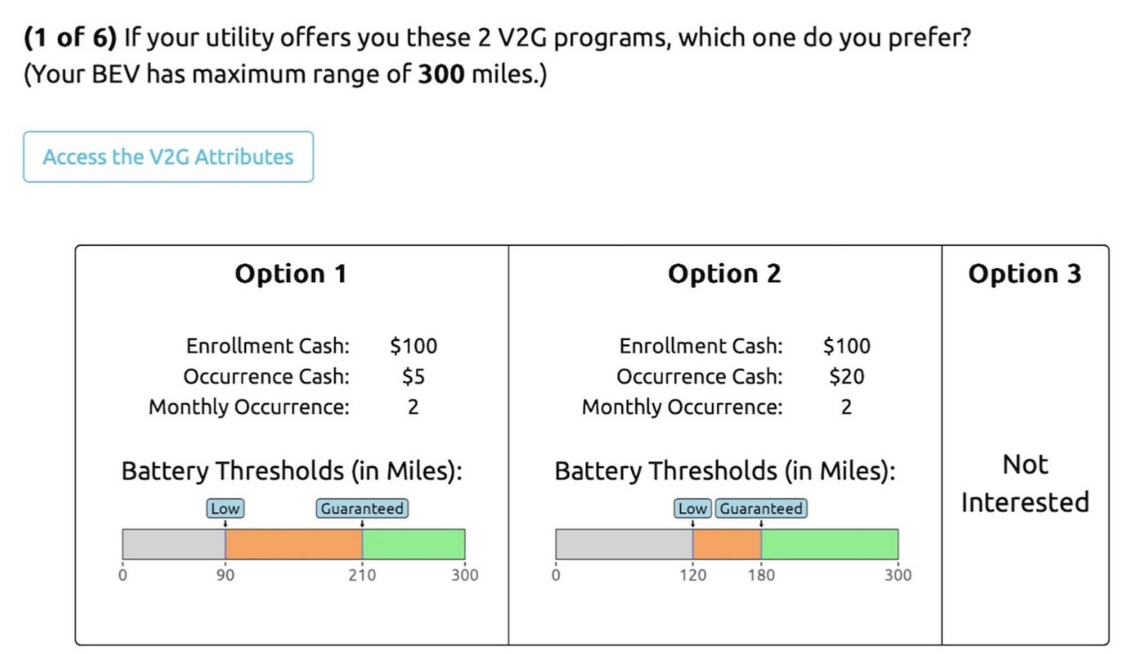

Figure 2. Sample V2G conjoint question. Each respondent was asked 6 choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

`logitr` R package (Helveston 2023). The survey was designed and published on https://formr.org Arslan *et al* (2020), R Core Team (2024), and all analyses were conducted using the R programming language. Tables of the estimated model coefficients are provided in *SMC logit model tables* and *V2G logit model tables* of the *supplementary information* section. We chose the MXL model because it relaxes the IIA (independence of irrelevant alternatives) assumption of the simpler MNL model (Train 2009), which assumes that the relative odds of choosing between any two alternatives are unaffected by the presence or attributes of other alternatives.

We present our primary findings from the MXL model in the section 3 section. For comparison and robustness testing, we also estimate two additional models detailed in the *supplementary information* section: a MNL model (see the *MNL plots* subsection), and a gender-weighted MXL model to assess sensitivity to gender imbalance in our sample (see the *gender-weighted MXL plots* subsection).

3. Results

Out of the 1,356 responses, 73% own at least two vehicles, 93% report regularly charging at home, and 51% use some form of UMC such as charging apps to schedule charging during off-peak periods (often to charge at a lower price in some locations). Very few (7%) respondents are enrolled in a SMC program, and 62% report caring about climate change very much. Our sample shows a gender skew with 73% male participants, consistent with BEV ownership generally (Chakraborty *et al* 2022). Additionally, 80% self-identify as White, 63% are under age 60, and 45% live in two-person households. Complete demographic and vehicle ownership characteristics are provided in the Supplementary Information.

Estimated coefficients of logit models are difficult to interpret directly, so to make them more accessible, we evaluate enrollment sensitivities to changes in each attribute through two-option simulations calculating the percentage of respondents predicted to opt into smart charging programs versus opting out. To isolate the effect of each attribute on enrollment sensitivity, we vary each attribute individually while holding all others constant at minimal values (zero for most attributes, or one where zero is not feasible, such as V2G monthly occurrences and occurrence payments).

Figure 3 reveals the relative enrollment sensitivity that BEV owners have toward changes in each attribute. The curves form an expected 'S' shape for logit models, with steeper slopes indicating greater sensitivity. For example, the *minimum threshold* for SMC is relatively flat, suggesting low sensitivity, while the *guaranteed threshold* and *monthly cash* both exhibit steeper slopes, indicating higher sensitivity. These curves quantify how enrollment responds to changes in each attribute when varied independently from minimal values.

The solid line in each plot reflect the range of attribute levels included in our survey, while dashed lines represent extrapolations and the gray bands represent 95% confidence intervals reflecting parameter uncertainty. In addition, the 'Override (Days)' attribute in SMC results has a kink at 1 day due to our modeling decision to include separate coefficients

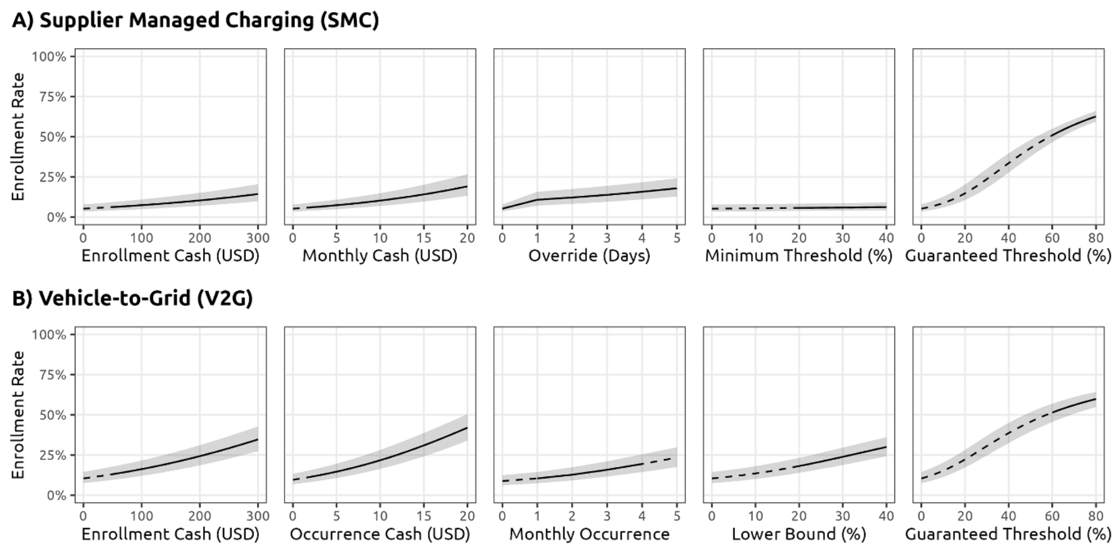

Figure 3. Sensitivity of smart charging program enrollment to changes in program attributes based on MXL model results. Solid lines indicate predictions within the ranges of attributes included in our survey, and dashed lines indicate extrapolations beyond the range of levels shown in the survey. Gray bands reflect 95% confidence intervals based on parameter uncertainty.

for 'having any override' and the 'number of override days,' reflecting the expected nonlinear relationship.

In each chart, the sensitivity curves start from the same enrollment level: 5.2% for SMC and 10.4% for V2G. These enrollment rates represent BEV owners with intrinsic willingness to participate even without incentives. To validate our model predictions, we compare against real-world enrollment data from a California SMC program, which achieved an enrollment level of 10% with a $40 monthly payment (Kobernick *et al* 2025). In our sensitivity curve, we see a 10% enrollment level with a monthly incentive of approximately $18. This suggests that our results overestimate the enrollment level compared to real-world experiments, perhaps due to discrepancies in the nature of the experiments (stated versus revealed preference) and also perhaps our particular sample, which may over-represent BEV owners that are more enthusiastic about BEVs and/or smart charging in general. Nevertheless, the relative sensitivities across attributes remain informative for program design.

While these sensitivity plots show how consumers respond to attribute changes, program designers need guidance for making trade-offs between different features. To facilitate this, we introduce an 'attribute equivalency' analysis to determine which changes in smart charging program attributes result in equivalent changes in predicted enrollment.

Given the nonlinear nature of enrollment sensitivities, we establish baseline scenarios for each program that yield approximately 50% enrollment, providing a reference point for calculating attribute trade-offs. For SMC simulations, the baseline scenario results in enrollment rate of 51%, including $50 *enrollment cash*, $2 *monthly cash*, 1 *override allowance* per month, and 20%/40% battery charging *minimum/guaranteed thresholds*. For V2G simulations, the baseline results in enrollment rate of 55%, including $50 *enrollment cash*, $2 per *occurrence*, 1 monthly *occurrence*, and 20%/40% *lower/guaranteed thresholds*.

Tables 3 and 4 show attribute equivalences for SMC and V2G programs. Each 'equivalency value' represents the change needed in that attribute to increase enrollment by 5%.

Table 3. SMC equivalencies of 5% enrollment increase.

Attribute	Equivalency value[a,b]
Enrollment cash ($)	77.7
Monthly cash ($)	4.0
Override days	2.5
Minimum threshold (%)	65.5
Guaranteed threshold (%)	6.3

[a] Applying baseline scenario predictions using the MXL model.
[b] Values show attribute changes for a 5% enrollment increase from 51% baseline.

Table 4. V2G equivalencies of 5% enrollment increase.

Attribute	Equivalency value[a,b]
Enrollment cash ($)	55.7
Occurrence cash ($)	2.9
Monthly occurrence	1.9
Lower bound (%)	11.7
Guaranteed threshold (%)	9.1

[a] Applying baseline scenario predictions using the MXL model.
[b] Values show attribute changes for a 5% enrollment increase from 55% baseline.

Smaller equivalency values indicate greater efficiency in achieving enrollment increases. The monetary incentives reveal consistent trade-offs between upfront *enrollment cash* and recurring payments. For SMC, an increase of \$4.0 in *monthly cash* achieves the same enrollment gain as a one-time upfront incentive of \$77.7, indicating that the monthly incentive is roughly 19 times more efficient. V2G shows similar patterns, with recurring payments demonstrating greater efficiency than one-time enrollment incentives.

For battery thresholds, guaranteed thresholds are more efficient in both programs, though the magnitude of this difference varies. In SMC programs, the *guaranteed threshold* only needs to increase by 6.3% to achieve a 5% enrollment increase, whereas the *minimum threshold* requires a 65.5% increase, suggesting BEV owners care far more about guaranteed range for daily needs than when smart charging starts. V2G shows a similar preference pattern but with a much smaller difference, requiring 9.1% and 11.7% changes for *guaranteed threshold* and *lower threshold* respectively, reflecting concerns about both battery health from deep discharging (Perger and Auer 2020, Liu and Zhang 2024) and available driving range.

Flexibility attributes show that 2.5 additional *override days* in SMC and 1.9 additional *monthly occurrences* in V2G each produce 5% enrollment increases. For SMC, this indicates that consumer control over opting out significantly increases program appeal. For V2G, this suggests that more opportunities to earn payments are valuable to consumers.

Program administrators ultimately need to choose combinations of attributes when establishing programs. We conducted scenario analyses comparing specific smart charging programs against the no-choice option, developing scenarios across three categories based on prior research (Geske and Schumann 2018, Huang *et al* 2021, Wong *et al* 2023): one-time cash incentives, recurring cash payments, and flexibility. For all scenarios, battery thresholds are set at 0%/40% to ensure meaningful program participation, with other attributes at minimal values (zero for most attributes, or one where zero is not feasible) unless otherwise specified.

Figure 4 shows expected enrollment rates across attribute levels used in prior research. The results demonstrate that flexibility is highly valued in SMC programs. Offering only flexibility through guaranteed battery thresholds and override options, with no monetary incentives, results in at least 45% enrollment. While monetary incentives drive acceptance, increasing override days has larger effects than equivalent monthly payments, suggesting payment-only SMC programs may be less successful than those combining payments with meaningful flexibility.

V2G dynamics differ significantly. Flexibility remains highly valued, but trade-offs with monetary incentives are less steep compared to SMC. High occurrence payments (\$20 per occurrence at four monthly occurrences) achieve 77% enrollment, suggesting BEV owners view V2G as an attractive income opportunity, which makes sense given that V2G participation directly generates revenue while SMC primarily offers modest payments.

4. Discussion

Our discrete choice experiment reveals important insights for designing grid-integration programs to attract sufficient BEV owner participation to transform vehicles from passive loads into active grid resources. Based on sensitivity and equivalency analyses of SMC and V2G program attributes, we identify key parameters for achieving designs that align with consumer preferences while supporting energy system decarbonization goals.

Recurring cash incentives are more efficient than one-time enrollment payments in both program types. Relatively small monthly incentives (\$4.0 and \$2.9 per month) generate equivalent enrollment impacts as \$77.7 and \$55.7 in one-time enrollment cash for SMC and V2G, respectively. This suggests utilities could achieve higher enrollment rates at lower costs through recurring payment mechanisms, such as dynamic rate structures or monthly grid service compensation. Prior real-world trials found that participation rates declined once recurring payments were removed (Bailey *et al* 2023), indicating sustained incentives may be important for maintaining long-term grid service availability.

The differing valuation of monetary incentives between SMC and V2G programs reveals important market design implications. V2G participants demonstrate stronger sensitivity to compensation levels, reflecting the more active role of providing bidirectional power flow. Higher valuation of monthly V2G events compared to SMC override days suggests V2G program designs could be structured around discrete grid service events, similar to existing demand response programs (Lehmann *et al* 2022), whereas SMC programs may benefit from simpler monthly subscription models.

Operational flexibility emerges as a critical design parameter in both programs. For SMC, the guaranteed threshold is much more valued than the minimum threshold, indicating range certainty is crucial for program acceptance. Relative indifference to minimum thresholds suggests utilities have significant latitude in when they initiate charging control, provided they ensure sufficient final charge levels. This gives utilities greater flexibility to align charging with renewable energy availability or grid capacity. For V2G, both lower and guaranteed thresholds significantly influence participation, reflecting legitimate concerns about battery degradation from bidirectional power flow (Perger and Auer 2020, Liu and Zhang 2024). V2G program designs must carefully

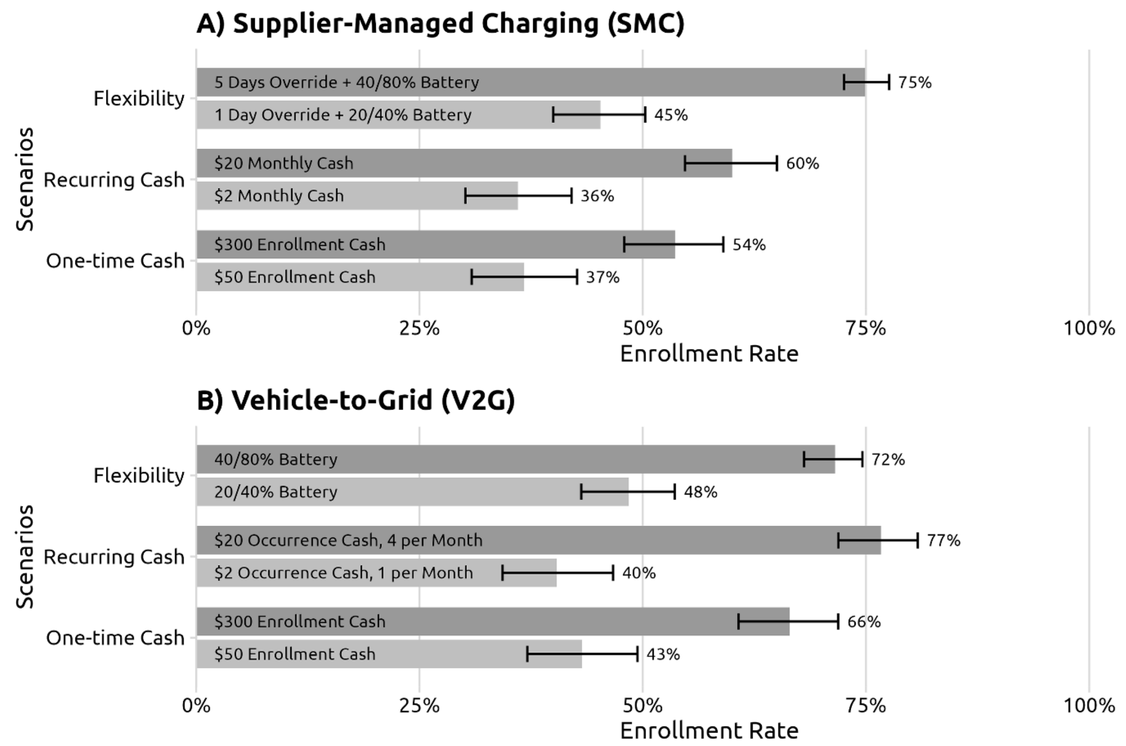

Figure 4. Predicted enrollment rates for various scenarios of SMC and V2G programs based on MXL model results. For both programs, we simulated three scenarios focusing on flexibility, recurring cash, and one-time cash incentives, with battery thresholds set at 0%/40% for meaningful participation unless otherwise specified. Each scenario includes both high and low cases.

balance grid services provided against battery lifetime impacts.

Our attribute equivalency analysis provides utilities clear guidance for cost-effective program design. A 5% increase in SMC enrollment can be achieved through either a $77.7 increase in one-time enrollment cash, a $4.0 increase in monthly payments, or a 6.3% increase in guaranteed charging threshold. For V2G programs, a $55.7 increase in enrollment cash equals a $2.9 increase in per-event compensation for achieving equivalent enrollment gains. These equivalencies reflect underlying preferences where range certainty and guaranteed outcomes strongly influence participation decisions. This complements recent evidence by Meyer *et al* (2022) that behavioral interventions can enhance the effectiveness of price-based demand management programs through educational communications and social norming strategies. Our findings suggest that smart charging program designs could leverage these behavioral insights by combining the attribute configurations identified in our study with targeted messaging that addresses range anxiety concerns and educates participants about program benefits and social comparisons with other participants.

Our findings have broader implications for policy frameworks governing distributed energy resources and consumer participation in grid services. Policymakers can support SMC and V2G adoption through incentive structures that reward utilities for integrating BEVs into grid operations. Building on utilities offering monetary incentives to customers, policymakers can provide utilities broader financial incentives, such as returns on smart grid investments, funding for pilot programs through customer rates, or revenue opportunities when BEVs support the grid. These can be implemented through performance-based regulation that ties utility compensation to program outcomes such as enrollment rates, grid service delivery, or avoided infrastructure costs. By aligning financial returns with measurable system benefits, policymakers can encourage utilities to actively support BEV integration as part of broader decarbonization strategies.

Our study is not without limitations. First, our study captures the preferences of current BEV owners, who represent earlier adopters with higher incomes and less demographic diversity than the general car-owning population (Borenstein and Davis 2016, Guo and Kontou 2021). Nonetheless, these individuals are also the most likely BEV owners to be eligible to participate in smart charging programs today as they typically own their own homes and have regular long-duration charging windows (e.g. overnight charging), which is necessary for smart charging programs to be effective. As BEV adoption broadens, program design parameters may require adjustment. Second, validating our findings against real-world smart charging programs remains challenging due to limited access to BEV ownership data in utility service territories. Our models may be optimistic in predicting higher enrollments than may occur in field experiments if other factors that we did not include in our experiment are important; for example, weak trust between participants and a given utility could negatively impact enrollment. Finally, our study focuses on consumer preferences rather than the technical and economic optimization of different grid services that could be provided through these programs.

To facilitate program design comparison across utility contexts, we developed an interactive web application using the `shiny` R package (Chang *et al* 2024) available at https://gwuvehicle.shinyapps.io/enrollment_simulator/, providing program designers the ability to compare expected enrollment under different configurations.

5. Conclusion

This study advances our understanding of how to incentivize BEV owners to participate in smart charging programs that enable utilities to optimize grid operations and facilitate renewable energy integration through controlled charging (SMC) or bidirectional power flow (V2G). Through a discrete choice experiment with 1,356 current BEV owners, we quantify the relative efficiency of different program attributes in driving enrollment. Our attribute equivalency analyses reveal that small changes in certain parameters (like guaranteed charging thresholds) can achieve the same enrollment impacts as larger changes in other parameters (like one-time payments), providing program designers and utility regulators clear guidance for cost-effective programs.

Our findings reveal distinct preference patterns across program types that inform both technical implementation and market design. SMC participants predominantly value operational flexibility and modest recurring payments, suggesting that programs that focus on guaranteed charging outcomes while maintaining predictable compensation would be attractive. V2G participants demonstrate stronger sensitivity to monetary incentives, reflecting the income-generating potential of bidirectional power flow. These insights help utilities optimize program costs against grid benefits while achieving meaningful participation rates.

Importantly, our focus on non-monetary properties of SMC and V2G programs shows that significant participation can be achieved without direct payments or subsidies for consumers, though some form of direct payment remains consistently useful for attracting participants. An interactive web application available at https://gwuvehicle.shinyapps.io/enrollment_simulator/ allows utility program designers to explore enrollment implications of different program designs. Future research should integrate these consumer preference models with power system optimization models to identify program configurations that maximize both grid benefits and consumer participation, ultimately accelerating the transition to a decarbonized energy system.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://github.com/jhelvy/smart-charging-preferences-2025.

Supplementary Information available at https://doi.org/10.1088/1748-9326/ae2597/data1.

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Ethical statement

This research involved human participants was conducted in accordance with our Institutional Review Board approved by the George Washington University (IRB ID: NCR245575). All participants provided informed consent to participate in the study.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used the Claude Sonnet 3.7 large language model in order to improve language for clarity and no other purpose. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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