A Thesis Proposal for the Degree of

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By

Pingfan Hu

B.S., Industrial & Manufacturing Engineering, Pennsylvania State University
M.P.E., Mechanical Engineering, Sydney University

Dissertation Committee

John Paul Helveston, Ph.D.
Caitlin Grady, Ph.D.
Johan René van Dorp, Ph.D.
Eric Hittinger, Ph.D.

Department of Engineering Management and Systems Engineering
The George Washington University
Washington, D.C.

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Essays on Electric Vehicle Smart Charging Preferences, Implications for the Grid, and an Introduction to the surveydown Survey Platform

Pingfan Hu

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Introduction

Electrified transportation substantially benefits the environment by reducing greenhouse gas emissions and decreasing the usage of fossil fuels (Elgowainy et al., 2018; Jenkins et al., 2021; Shukla et al., 2022) . However, the large-scale adoption of Battery Electric Vehicles (BEVs) introduces new demand on the electricity grid that must be carefully managed to avoid exacerbating peak load challenges or requiring costly infrastructure expansions. The timing of BEV charging represents a critical factor that can either strain grid resources or, if properly managed, provide valuable flexibility services that support renewable energy integration and grid stability.

While much technical research has explored the theoretical potential of "smart charging" programs to better manage BEV charging, significant gaps remain in our understanding of consumer preferences for such programs, design requirements for these programs, and the cost-effectiveness considerations necessary for successful real-world implementation. This dissertation addresses these gaps through a multidisciplinary approach that combines empirical consumer research, systems engineering analysis, and methodological innovation.

The first study examines consumer preferences for two key smart charging strategies: Supplier-Managed Charging (SMC), which enables utilities to optimize charging timing, and Vehicle-to-Grid (V2G) systems, which transform BEVs into distributed energy storage resources. Through a discrete choice experiment with 1,356 current BEV owners, this study quantifies how different program attributes influence participation decisions, revealing distinct preference structures for SMC and V2G programs. The findings provide critical insights for developing market mechanisms and policy frameworks that align consumer preferences with grid optimization objectives.

Building on these consumer insights, the second study addresses a critical gap in existing research by evaluating the true cost-effectiveness of BEV grid support programs when realistic enrollment costs and participation rates are considered. While previous research has documented the technical potential of smart charging, these analyses often overlook practical implementation barriers, potentially creating unrealistic expectations about grid benefits. This study develops a comprehensive framework for evaluating BEV grid support strategies that accounts for enrollment costs, participation rates, and peak load reduction potential.

Finally, the third study addresses methodological challenges in conducting sophisticated survey research by introducing **surveydown**, an open-source, markdown-based survey platform built in the R programming language. This methodological innovation enables programmable and reproducible surveys that support complex experimental designs, adaptive questioning, and transparent research practices. The development of this platform addresses limitations in existing survey tools and provides the broader community of survey researchers with enhanced capabilities for conducting rigorous empirical studies.

Collectively, these three studies pursue the following primary research questions:

1. How do changes in smart charging program features influence BEV owners' willingness to participate, and under what conditions will BEV owners be more willing to opt in to smart charging programs?

2. How does the cost-effectiveness of supplier-managed charging programs vary with consumer enrollment patterns and regional grid characteristics?

3. How can survey research methodologies be enhanced through open-source platforms that support programmability, reproducibility, and complex experimental designs?

Through addressing these questions, this dissertation contributes to both scholarly understanding and practical implementation of sustainable transportation systems. The findings provide actionable insights for utilities, policymakers, and technology developers seeking to maximize the grid benefits of transportation electrification while ensuring that program designs align with consumer preferences and economic constraints. Additionally, the methodological contributions advance the broader scientific community's capacity to conduct rigorous, transparent, and reproducible research on consumer behavior and technology adoption.

The following chapters detail each study's theoretical foundations, methodological approaches, findings, and implications. Together, they illustrate how interdisciplinary perspectives and innovative methods can address complex challenges at the intersection of consumer behavior, technology adoption, and systems optimization in the context of sustainable transportation.

Overview of Dissertation Studies

The electrification of transportation represents a pivotal strategy in global efforts to reduce greenhouse gas emissions and dependence on fossil fuels. Research indicates that BEVs can significantly reduce vehicle lifecycle emissions compared to conventional vehicles, with reductions of up to 30% per vehicle in general (Elgowainy et al., 2018). These benefits are expected to increase as electricity generation continues to decarbonize through expanded renewable energy deployment.

However, the environmental benefits of BEVs are contingent on both the emissions intensity of electricity sources and the timing of vehicle charging. Studies have demonstrated that uncoordinated BEV charging typically coincides with existing peak electricity demand periods, potentially increasing grid stress, infrastructure costs, and even emissions when peaking generators are dispatched (Zhang et al., 2020). This challenge becomes increasingly significant as BEV adoption scales, with multiple studies highlighting the potential impacts on distribution systems and generation capacity requirements if charging remains unmanaged. One representational study in California indicates that EVs may use up to 60% of renewable capacity under immediate charging, but with smart charging, this requirement drops significantly (Forrest et al., 2016).

This dissertation addresses these challenges through three interconnected studies. First, we examine consumer preferences for smart charging programs among current BEV owners, quantifying how different program attributes influence participation in both Supplier-Managed Charging (SMC) and Vehicle-to-Grid (V2G) programs. Second, we develop a framework for evaluating the true cost-effectiveness of the SMC program as a representative smart charging program, by accounting for realistic enrollment costs and participation rates—factors often overlooked in technical potential analyses. Finally, we introduce methodological innovations through the development of surveydown, an open-source survey platform that enhances researchers' ability to conduct complex, reproducible surveys critical for understanding consumer preferences and behavior.

Together, these studies advance both our understanding of BEV grid integration and the methodological tools available for transportation electrification research. By bridging consumer preferences, implementation economics, and research methodologies, this work provides a comprehensive approach to accelerating sustainable transportation transitions while optimizing grid integration.

Study 1: Electric Vehicle Owner Preferences for Smart Charging Programs

Research Question 1: How do changes in smart charging program features influence BEV owners' willingness to opt in; and under what conditions will BEV owners be more willing to opt in to smart charging programs?

As shown in Figure 1, smart charging avoids peak load. The success of smart charging strategies fundamentally depends on BEV owners' willingness to participate. Prior research suggests that most owners are hesitant to enroll without adequate incentives, citing concerns about privacy, operational limitations, and insufficient compensation (Bailey and Axsen, 2015; Sovacool et al., 2018). However, many previous studies have relied on data from general vehicle owners who lack direct experience with BEV charging, potentially limiting their ability to accurately assess program trade-offs.

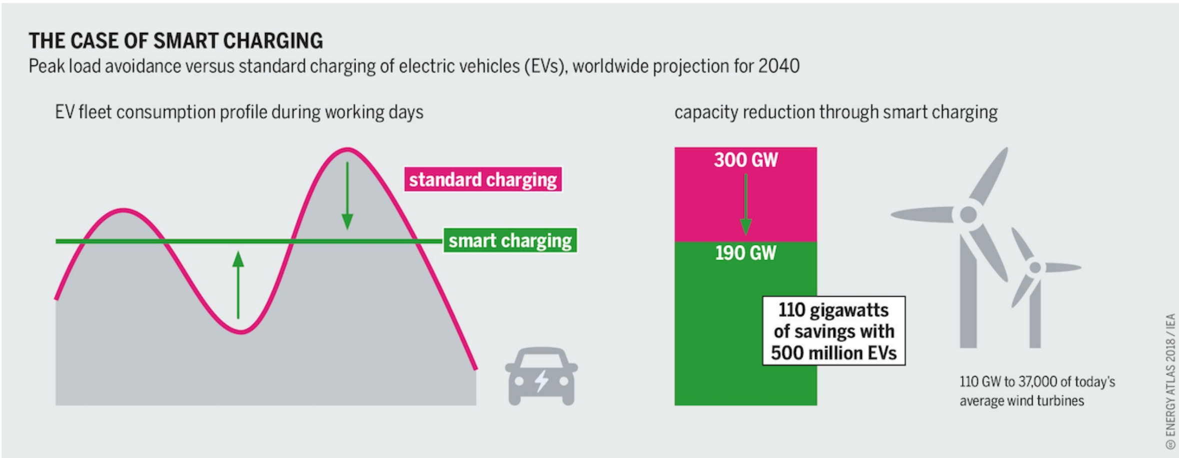


Figure 1: Smart charging helps avoid peak load (Bartz and Stockmar, 2025).

Recent studies have begun to explore the factors influencing smart charging program acceptance. Wong et al. (2023) examined how incentive structures affect program participation using a discrete choice experiment, finding that while monetary incentives are important, there are diminishing returns to continued payment increases. Philip and Whitehead (2024) found that guaranteed driving range significantly influences participation willingness, while Huang et al. (2021) showed that V2G participation increases when rapid recharging is available, making access to level-2 charging infrastructure essential.

However, a critical limitation of these prior studies is their reliance on samples primarily drawn 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. Furthermore, many vehicle owners would be ineligible for smart charging programs due to lack of regular access to overnight charging. The first study in this dissertation addresses this gap by focusing exclusively on real BEV owners, providing more reliable insights into the preferences of those who would actually be eligible for smart charging programs.

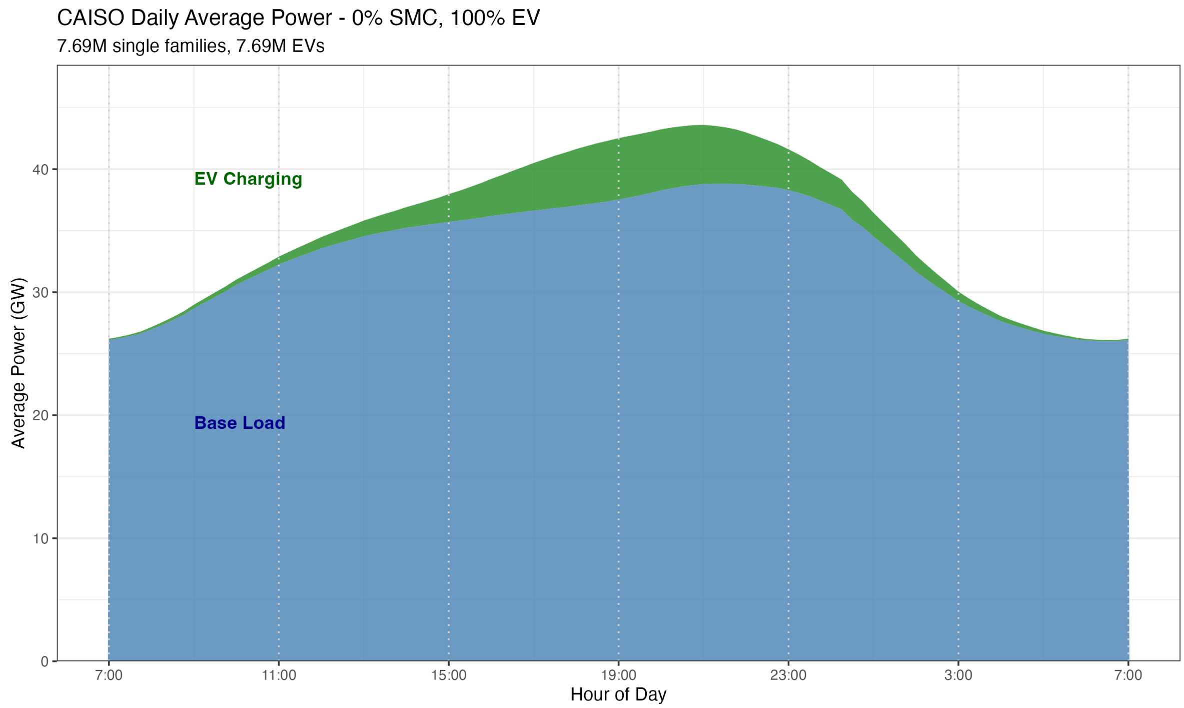
Study 2: Cost-Effectiveness of Supplier-Managed Charging Programs

Research Questions: What are the cost-benefit trade-offs for utilities implementing these programs? How do these trade-offs vary across different locations?

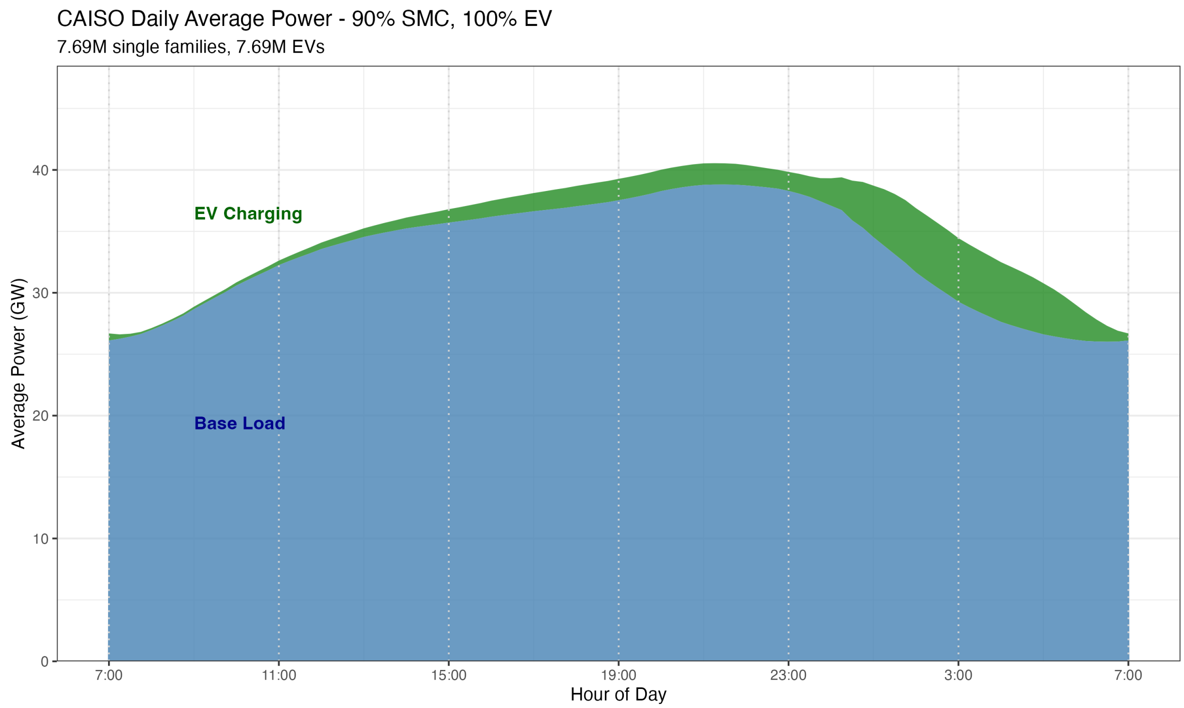
Smart charging programs represent a critical demand response strategy for managing the grid impacts of large-scale electric vehicle adoption, and supplier-managed charging (SMC) is a common approach of smart charging. However, existing literature exhibits a significant gap between theoretical assessments of smart charging potential and realistic evaluations under practical implementation constraints. Most studies assume optimal participation rates and minimal implementation costs (Tarroja et al., 2015; Coignard et al., 2018), creating uncertainty for utilities and policymakers seeking to develop economically viable programs. Implementation barriers include enrollment rates, incentive costs, facility costs, and ongoing program management, which can substantially offset grid benefits (Bailey and Axsen, 2015).

This study addresses these limitations through development of a comprehensive regional cost-effectiveness framework that incorporates consumer enrollment models and region-specific grid characteristics. The consumer enrollment models are generated by Study 1. The research synthesizes three data sources: National Household Travel Survey (NHTS) data for vehicle trip patterns, National Renewable Energy Laboratory (NREL) Cambium 2024 data for electricity consumptions of all 18 Grid Emissions Analysis (GEA) regions across the U.S., and consumer preference models from survey research in Study 1 quantifying willingness to participate.

The simulation framework employs Monte Carlo methods to model electric vehicle charging behavior under various smart charging strategies, utilizing valley-filling algorithms that shift charging demand to off-peak periods. The ideal shifting is to shave the peak in the evening and relocate to early morning. Completed analyses for three representative regions (CAISO, NYISO, PJM East) demonstrate substantial load shifting potential, with peak demand reductions of 10-15% with high SMC enrollment rates. As an interim result, Figure 2 below shows the daily load profiles of the CAISO grid before and after SMC enrollment.



(a) With no SMC enrollment, the CAISO grid peaks at 43GW in the evening.



(b) An 90% SMC enrollment can shave the peak to 41GW by relocating the load to early morning.

Figure 2: Daily load profiles of the CAISO grid before and after SMC enrollment.

The extent of peak shaving is dependent on the percentage of BEV owners enrolled in SMC programs as well as the base load profile of each region. The cost of peak shaving, however, is dependent of the incentive costs for enrollment, and the varied electricity prices across regions. Economic breakeven points are yet to be calculated, and are expected to have regional variations reflecting differences in electricity prices, peak demand profiles, and percentages of BEV adoption. Starting from a simple monthly incentive model, we sketched the cost of peak shaving performance. Figure 3 below shows the cost-effectiveness of monthly cash incentives for the CAISO grid.

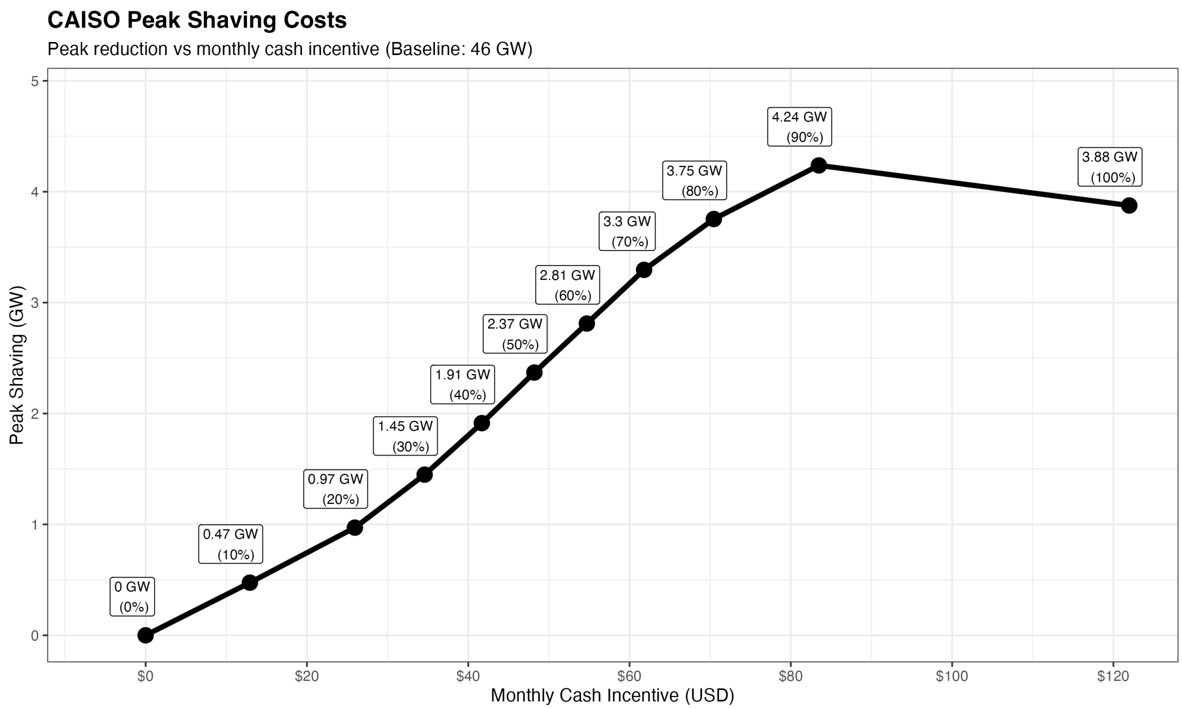


Figure 3: Peak shaving cost-effectiveness for the CAISO grid.

Different from CAISO, NYISO peaks 2 hours earlier and results in better peak shaving performance. This brings the necessity of regional analysis. We will eventually complete the peak shaving cost-effectiveness analysis for all 18 GEA regions in the U.S. The results will provide utilities and policymakers with realistic expectations of SMC program benefits and costs, informing the design of economically viable programs that effectively leverage BEV flexibility to support grid operations.

Study 3: Methodological Innovation for Survey Research

Research Question 3: How can survey research methodologies be enhanced through open-source platforms that support programmability, reproducibility, and complex experimental designs?

Robust empirical research on consumer preferences and behavior is essential for developing effective grid-integration programs. However, conducting sophisticated survey experiments with complex randomization, conditional logic, and interactive elements presents significant methodological challenges. As shown in Figure 4, existing survey platforms often impose limitations on reproducibility, data control, and other usability features.

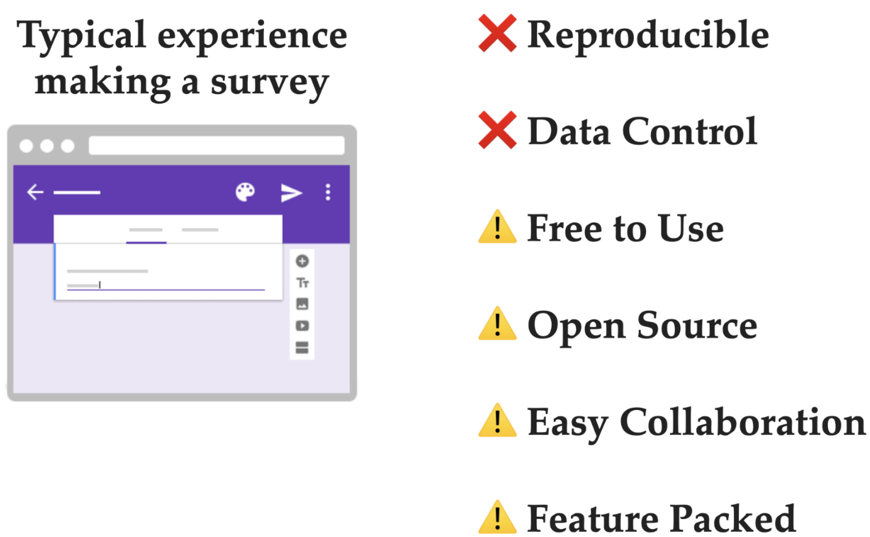


Figure 4: Limitations of typical survey platforms.

Most commercial survey platforms rely on graphical interfaces or spreadsheets to define survey content, making version control, collaboration, and reproducibility difficult. The commonly used Google Forms is a good example of it: a quick, easy survey can be produced using the intuitive GUI of Google Forms, but it is not reproducible, and features are highly limited. This creates barriers to transparent research practices and limits the complexity of experimental designs. Furthermore, many platforms offer limited control over data storage and extraction, potentially compromising long-term research integrity and complicating data analysis workflows. Qualtrics, for example, is a popular survey platform that offers many features, but it is not open-source and does not allow for reproducibility (Qualtrics, 2024).

The third study in this dissertation addresses these methodological challenges by developing surveydown, an open-source survey platform that enables programmable and reproducible surveys. By leveraging markdown and R code, this platform supports complex experimental designs while maintaining full transparency and reproducibility. This methodological innovation enhances the capacity to conduct rigorous consumer research not only in the transportation electrification domain but across diverse fields requiring sophisticated survey implementations.

Dissertation Research Contributions

This dissertation addresses three critical gaps in the existing literature on sustainable transportation systems through an integrated research framework that combines consumer research, systems analysis, and methodological innovation:

1. **Consumer Preference Insights**: While technical analyses have documented the grid benefits of managed charging, limited research has examined the preferences of actual BEV owners regarding grid-integration programs. The first study provides insights specific to current BEV owners, quantifying attribute trade-offs in program design and identifying program configurations that could enable widespread adoption.

2. **Cost-Effectiveness Evaluation**: Existing research typically presents optimistic assessments of grid-integration benefits without adequately accounting for implementation costs and participation constraints. The second study develops a comprehensive framework for evaluating the true cost-effectiveness of different grid support strategies under realistic conditions.

3. **Methodological Innovation**: Survey research on complex consumer decisions requires sophisticated tools that support experimental designs, conditional logic, and reproducibility. The third study introduces an open-source platform that enhances methodological capabilities while promoting transparent and reproducible research practices.

Through addressing these gaps, this dissertation contributes to both scholarly understanding and practical implementation of sustainable transportation systems. The findings inform utility program design, policy development, and technology innovation, ultimately supporting the transition to cleaner, more efficient transportation and energy systems.

The study on EV owner preferences for smart charging programs yields a collection of grid planning and policy implications. The grid integration strategies of SMC and V2G represent two distinct approaches to managing BEV charging, each with unique consumer preferences. The findings suggest that SMC participants value operational flexibility and recurring payments, while V2G supporters prefer monetary incentives, indicating a willingness to provide grid services for compensation. This distinction has important implications for program design and market mechanisms.

The study on cost-effectiveness of SMC programs is a further exploration of this field: even though the EV owners are willing to participate, the effectiveness of SMC should still be quantified and evaluated to prove its sustanability. This study converges two impacts from the SMC programs: 1) the peak load caused by unmanaged EV charging will be largely shaved to reduce electricity spike; 2) grids will benefit from reduced cost due to a larger share of electricity generation during low-demand time window.

These two studies focused on consumer and grid perspectives respectively, and together they provide a consolidated policy implication for utilities and policymakers seeking to leverage BEV flexibility to support grid operations. The findings highlight the importance of aligning program designs with consumer preferences while ensuring economic viability through realistic cost-benefit analyses.

The surveydown platform was created along with these two studies on EV charging integration due to the frustration of the existing survey platforms. We have been searching for open-source, easy to use survey platforms and ended up with building our own. We are also motivated by the recent legislative momentum, in which congressional support for open-source tools is increasing (U.S. Congress, 2023, 2024). The surveydown platform fills this need for survey research.

Proposed Timeline

Studies 1 and 3 are complete, and Study 2 is ongoing. The expected timeline is as follows:

- October 2025: Complete simulation and cost-effectiveness calculation for Study 2.
- November 2025: Complete draft manuscript for Study 2.
- December 2025: Submit manuscript for Study 2 for journal peer review.
- March 2026: Defend dissertation.

The remainder of this proposal provides greater detail on the progress of each study. For Studies 1 and 3, full papers are included (1 is under review, and 3 is already published). For Study 2, a draft of current progress results are attached.

Study 1

This study has been submitted to *Environmental Research Letters (ERL)*, published by the Institute of Physics (IOP).

Measuring Electric Vehicle Owners' Willingness to Participate in Smart Charging Programs

Pingfan Hu[1]

Brian Tarroja, Ph.D., P.E.[2]

Matthew Dean, Ph.D.[2]

Kate Forrest, Ph.D.[2]

Eric Hittinger, Ph.D.[3]

Alan Jenn, Ph.D.[4]

John Paul Helveston, Ph.D.[1*]

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[1]Department of Engineering Management & Systems Engineering, George Washington University, DC 20052, USA.

[2]Department of Civil & Environmental Engineering, University of California, Irvine, CA 92697, USA.

[3]Department of Public Policy, Rochester Institute of Technology, NY 14623, USA.

[4]Institute of Transportation Studies, University of California, Davis, CA 95616, USA.

[*]Correspondence: jph@gwu.edu

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.

Keywords: Grid integration, Supplier-managed charging, Vehicle-to-grid, Energy storage, Smart charging, Consumer preferences, Discrete choice experiment

Highlights:

- Largest survey (N=1,356) on EV owner preferences for grid-integration programs
- Quantify how smart charging and V2G program attributes influence participation
- Reveal distinct preference: flexibility drives SMC while compensation drives V2G
- Developed attribute equivalencies to facilitate grid-integration program design

Introduction

The integration of Battery Electric Vehicles (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., 2020, 2011), potentially increasing grid stress, infrastructure costs, and greenhouse gas (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 (Forrest et al., 2016; Tarroja et al., 2015; Xu et al., 2025). Two key approaches have emerged: Supplier-Managed Charging (SMC), which enables utilities to optimize charging timing and duration while ensuring batteries reach desired charge levels by predefined times (Dean and Kockelman, 2024a), and Vehicle-to-Grid (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 and Hittinger, 2021; Tarroja et al., 2015).

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, 2024b). 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 (Wong et al., 2023; Parsons et al., 2014; Kubli, 2022; Lavieri and de Oliveira, 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 = 1,356) 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.

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 1,748 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; Walker et al., 2018; Eendebak and Schoen, 2017), 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 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 Table 1 and Table 2, and Figure 1 and Figure 2 show example choice questions for the SMC and V2G questions.

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 Dean and Kockelman (2024a); Wong et al. (2023) 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.

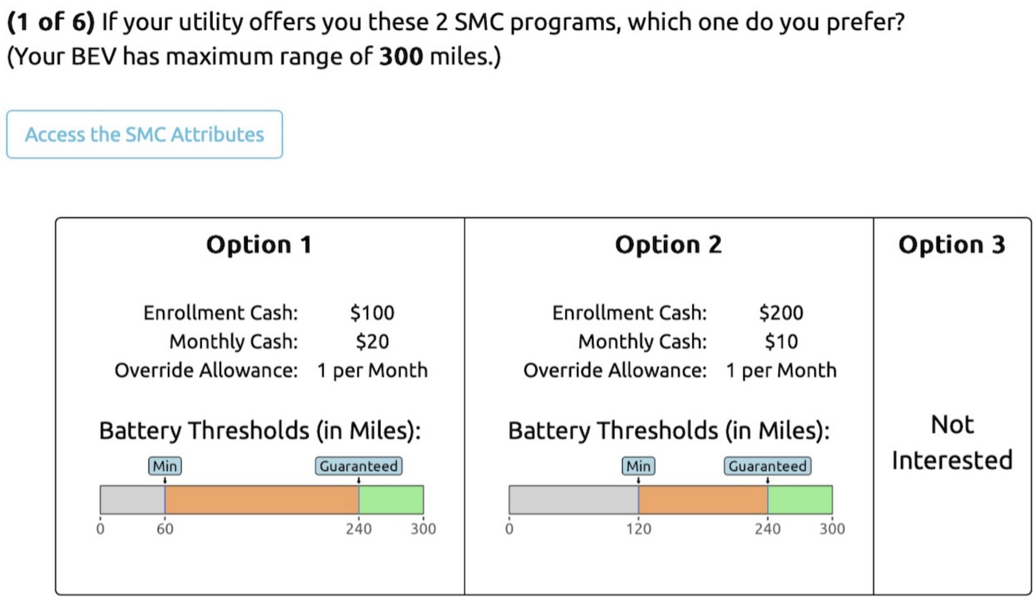

Figure 1: Sample SMC Conjoint Question. Each respondent was asked 6 SMC choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

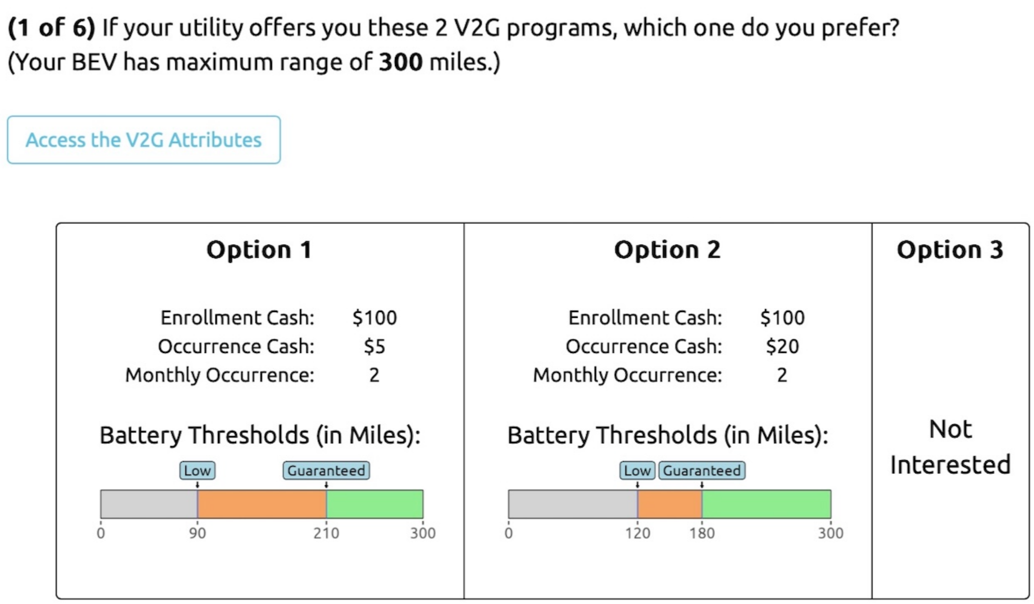

Figure 2: Sample V2G Conjoint Question. Each respondent was asked 6 V2G choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

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 1,356 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:

$$\begin{aligned} u_j = \beta_1 x_j^{\text{enroll\_cash}} &+ \beta_2 x_j^{\text{monthly\_cash}} + \beta_3 \delta_j^{\text{override\_allowed}} * \beta_4 x_j^{\text{num\_overrides}} \\ &+ \beta_5 x_j^{\text{min\_threshold}} + \beta_6 x_j^{\text{guaranteed\_threshold}} \\ &+ \beta_7 \delta_j^{\text{no\_choice}} + \epsilon_j \end{aligned} \tag{3}$$

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 ($x_j^{\text{num\_overrides}}$). 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:

$$
\begin{aligned}
u_j = \beta_1 x_j^{\text{enroll\_cash}} &+ \beta_2 x_j^{\text{occur\_cash}} + \beta_3 x_j^{\text{num\_occurrences}} \\
&+ \beta_4 x_j^{\text{lower\_threshold}} + \beta_5 x_j^{\text{guaranteed\_threshold}} \\
&+ \beta_6 \delta_j^{\text{no\_choice}} + \epsilon_j
\end{aligned} \tag{4}
$$

We estimated multinomial logit (MNL) models for each smart charging program via maximum likelihood estimation using the `logitr` R package (Helveston, 2023). The survey was designed and published on 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 the Supplementary Information.

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 user-managed charging (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 supplier-managed charging (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. For SMC simulations, the baseline scenario includes \$50 *Enrollment Cash*, \$2 *Monthly Cash*, 1 *Override Allowance* per month, and 20%/60% battery charging *Minimum/Guaranteed Thresholds*. For V2G simulations, the baseline includes \$50 *Enrollment Cash*, \$2 per *Occurrence*, 1 monthly *Occurrence*, and 20%/60% *Lower/Guaranteed Thresholds*.

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* shows high sensitivity. Solid lines reflect the range of attribute levels included in our survey, while dashed lines represent extrapolations and the gray bands represent 95% confidencne intervals reflecting parameter uncertainty. The “Override (Days)” attribute in SMC results has a kink at 1 day due to our modeling decision to include separate coefficients for "having any override" and the "number of override days", reflecting the expected nonlinear relationship.

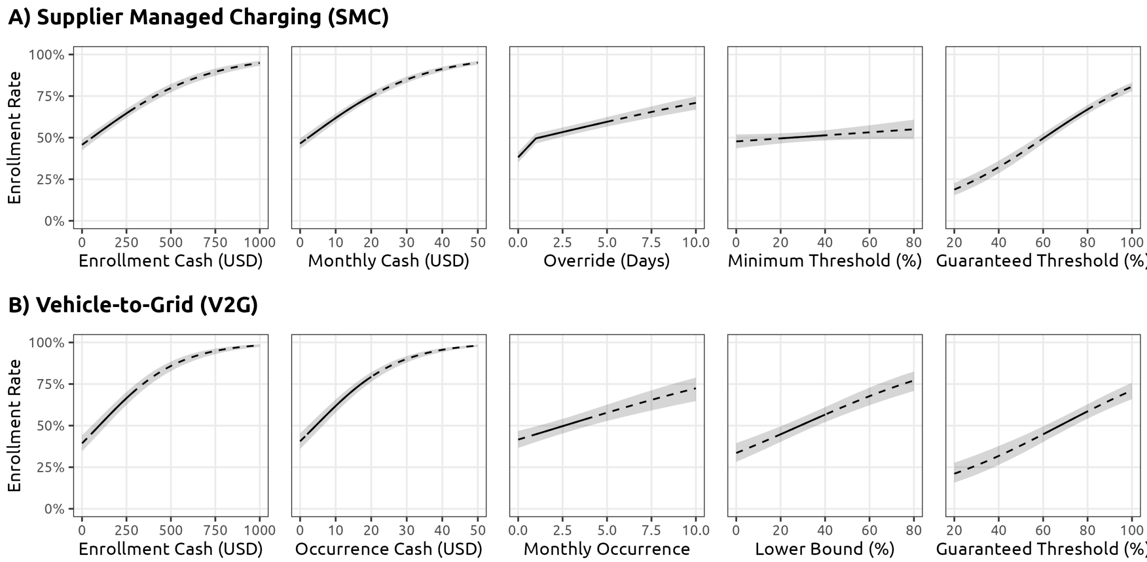

Figure 3: Plots of smart charging program enrollment sensitivity to changes in program attributes. Solid lines indicate predictions within the ranges of attributes included in our survey, and dashed lines indicate extrapolations beyond the range of levels shown in the survey. Gray bands reflect 95% confidence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

While 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. Using the same baseline scenarios (resulting in 50% predicted enrollment for SMC and 45% for V2G), we vary each attribute continuously until achieving a 5% increase in enrollment from baseline. Table 3 and Table 4 show attribute equivalences for SMC and V2G programs. Each "equivalency value" represents the change needed in that attribute to increase enrollment by 5%. Small equivalency values indicate large efficiency in terms of program enrollment.

Table 3: SMC Equivalencies of 5% Enrollment Increase

Attribute	Equivalency Value
Enrollment Cash ($)	64.7
Monthly Cash ($)	3.2
Override Days	2.0
Minimum Threshold (%)	54.8
Guaranteed Threshold (%)	5.5

1. *Predictions are based on the estimated MNL model*
2. *Equivalency values are based on the attribute changes needed to achieve a 5% increase in enrollment from the baseline rate of 50%.*

Table 4: V2G Equivalencies of 5% Enrollment Increase

Attribute	Equivalency Value
Enrollment Cash ($)	45.5
Occurrence Cash ($)	2.3
Monthly Occurrence	1.5
Lower Bound (%)	8.5
Guaranteed Threshold (%)	7.2

1. *Predictions are based on the estimated MNL model*
2. *Equivalency values are based on the attribute changes needed to achieve a 5% increase in enrollment from the baseline rate of 45%.*

The monetary incentives reveal consistent trade-offs between upfront *Enrollment Cash* and ongoing payments. For SMC, an upfront incentive of $64.70 produces the same enrollment increase as increasing *Monthly Cash* by $3.20, suggesting approximately 20 months of monthly payments equals one-time upfront incentives. V2G shows similar patterns: increasing *Enrollment Cash* by $45.50 equals increasing *Occurrence Cash* by $2.30, again yielding a 20-to-1 ratio. This consistency across survey topics suggests stable consumer time-value preferences.

Battery threshold results reveal important preferences. In SMC programs, the *Guaranteed Threshold* only needs to increase by 5.5% to achieve a 5% enrollment increase, whereas the *Minimum Threshold* requires a 54.8% increase. This suggests BEV owners care more about guaranteed range for daily needs than when smart charging starts. V2G shows different patterns, with similar changes required for both *Lower Threshold* and *Guaranteed Threshold* (8.5% and 7.2%, respectively), reflecting concerns about battery health from deep discharging (Liu and Zhang, 2024; Perger and Auer, 2020) and available driving range.

Flexibility attributes show that 2 additional *Override Days* in SMC and 1.5 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 (Wong et al., 2023; Geske and Schumann, 2018; Huang et al., 2021): one-time cash incentives, recurring cash payments, and flexibility. For all scenarios, default battery thresholds are set at 20%/60%, with other attributes at zero unless 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 50% 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 82% 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.

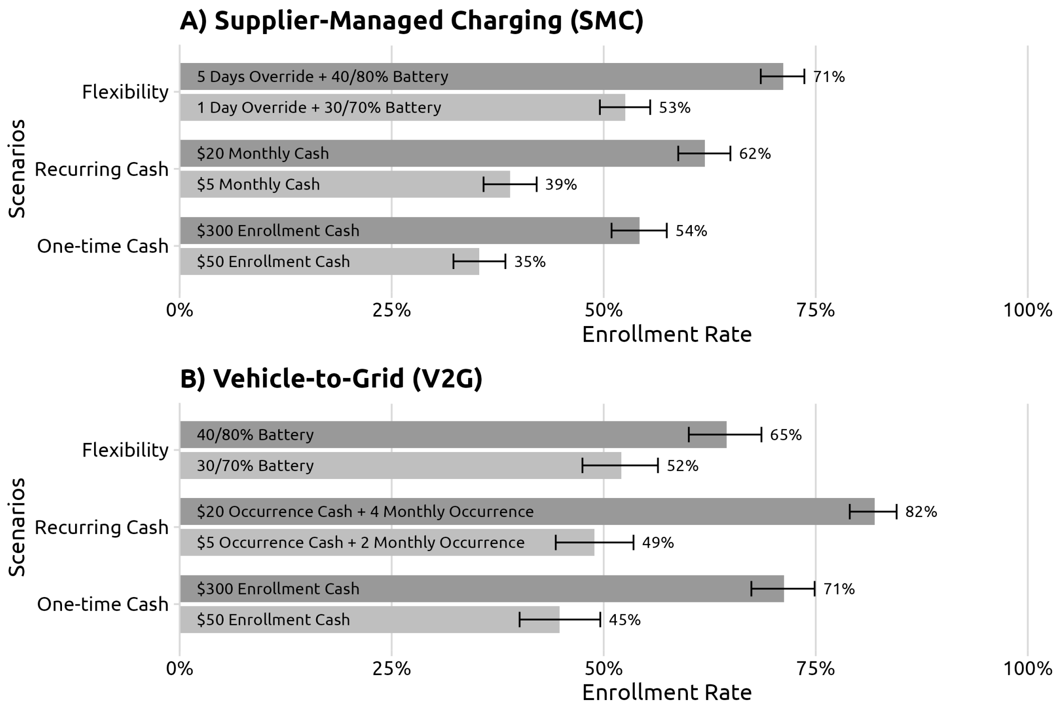

Figure 4: Scenario analyses of SMC and V2G programs. For both programs, we simulated three scenarios focusing on flexibility, recurring cash, and one-time cash incentives. Each scenario includes both high and low cases.

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 ($2-$3 per month) generate equivalent enrollment impacts as $65 and $46 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 (Liu and Zhang, 2024; Perger and Auer, 2020). V2G program designs must carefully 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 $65 increase in one-time enrollment cash, a $3.20 increase in monthly payments, or a 5.5% increase in guaranteed charging threshold. For V2G programs, a $45.50 increase in enrollment cash equals a $2.30 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 need 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.

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 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.

Glossary

- **BEV:** Battery Electric Vehicle
- **CV:** Conventional Vehicle, referring to non-hybrid gasoline-powered internal combustion engine vehicles
- **GHG:** Greenhouse Gas
- **MLE:** Maximum Likelihood Estimation
- **MNL:** Multinomial Logit
- **SMC:** Supplier-Managed Charging
- **UMC:** User-Managed Charging
- **V2G:** Vehicle-to-Grid

Data Availability

All code and data used in this study are publicly available on GitHub at: https://github.com/jhelvy/smart-charging-preferences-2025

Acknowledgments

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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.

Appendix

Demographics Summary

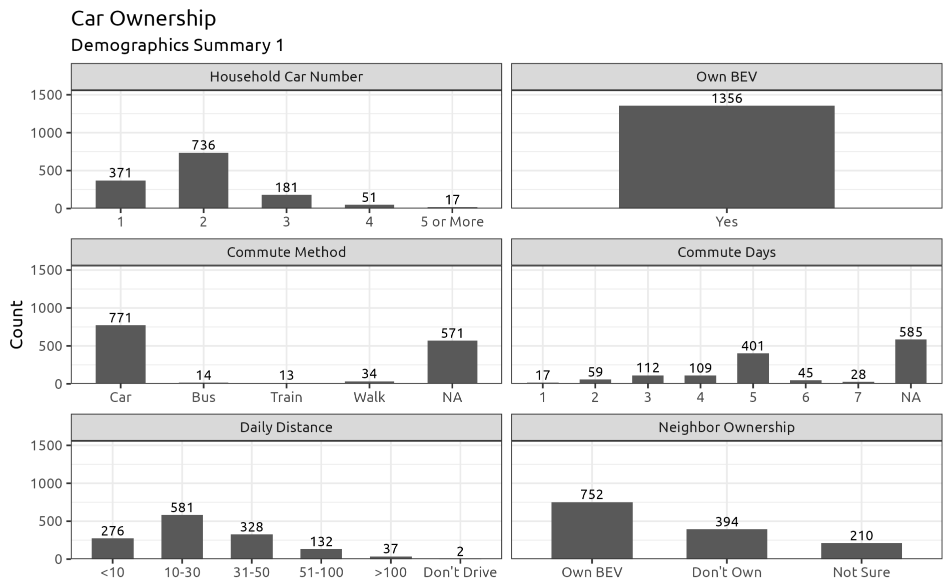

Figure A.1: Car Ownership

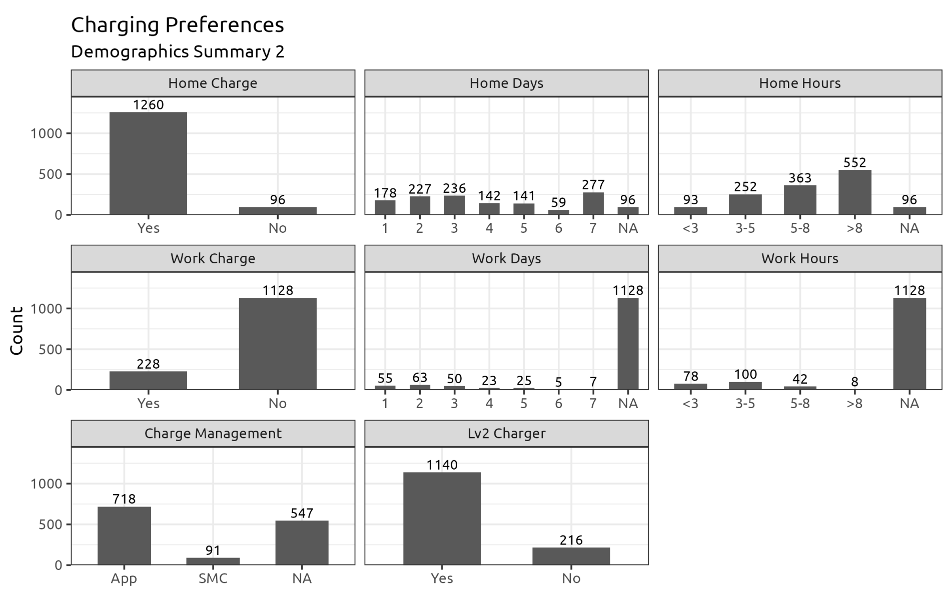

Figure A.2: Charging Preferences

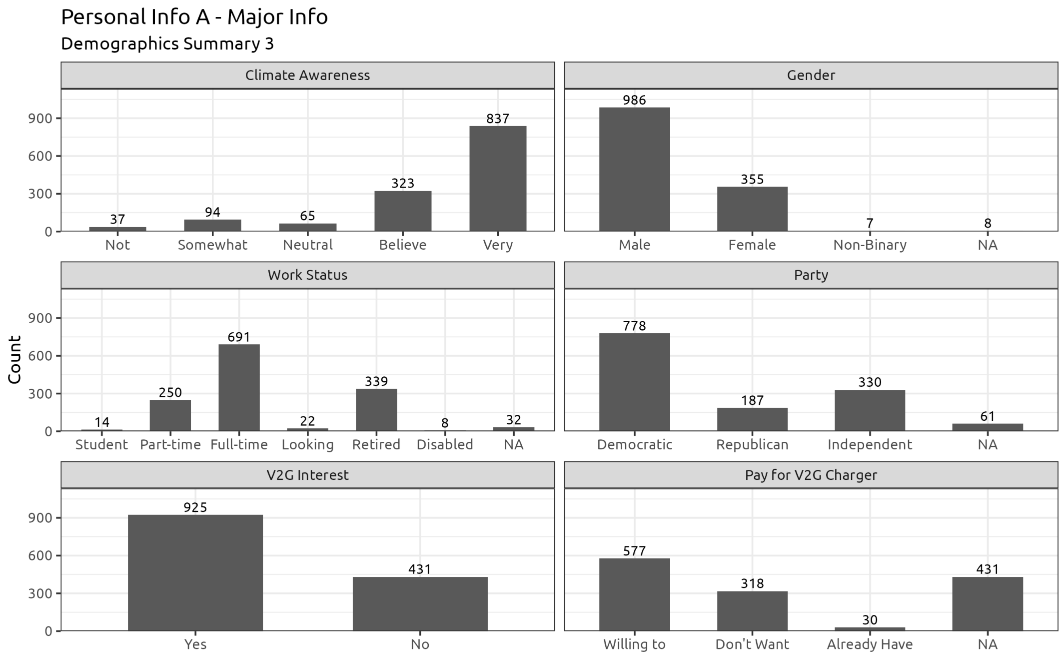

Figure A.3: Personal Info A - Major Info

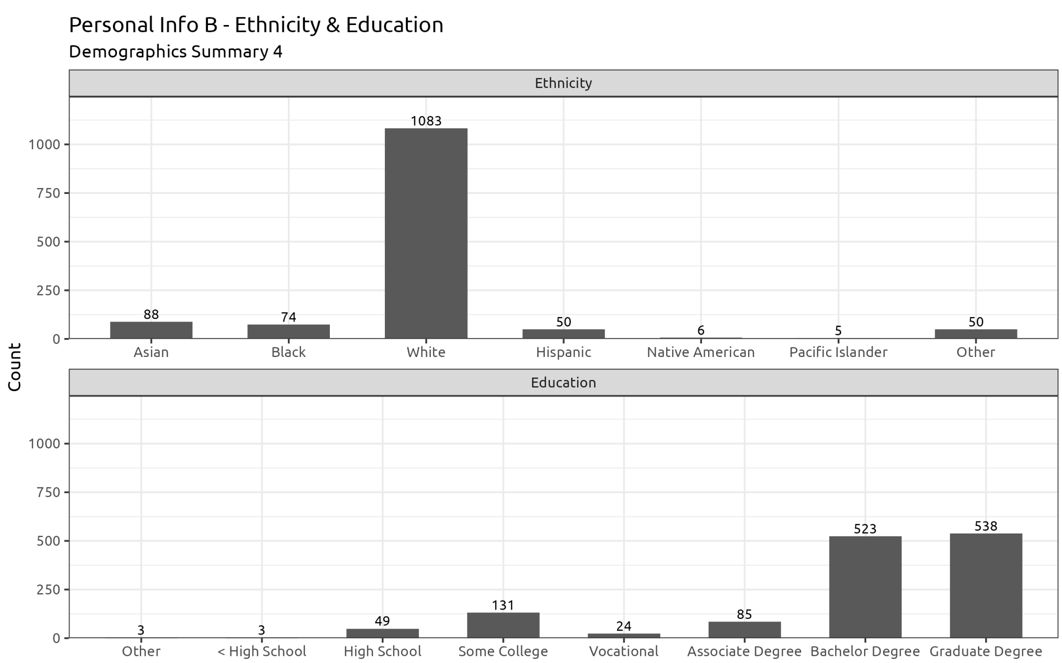

Figure A.4: Personal Info B - Ethnicity & Education

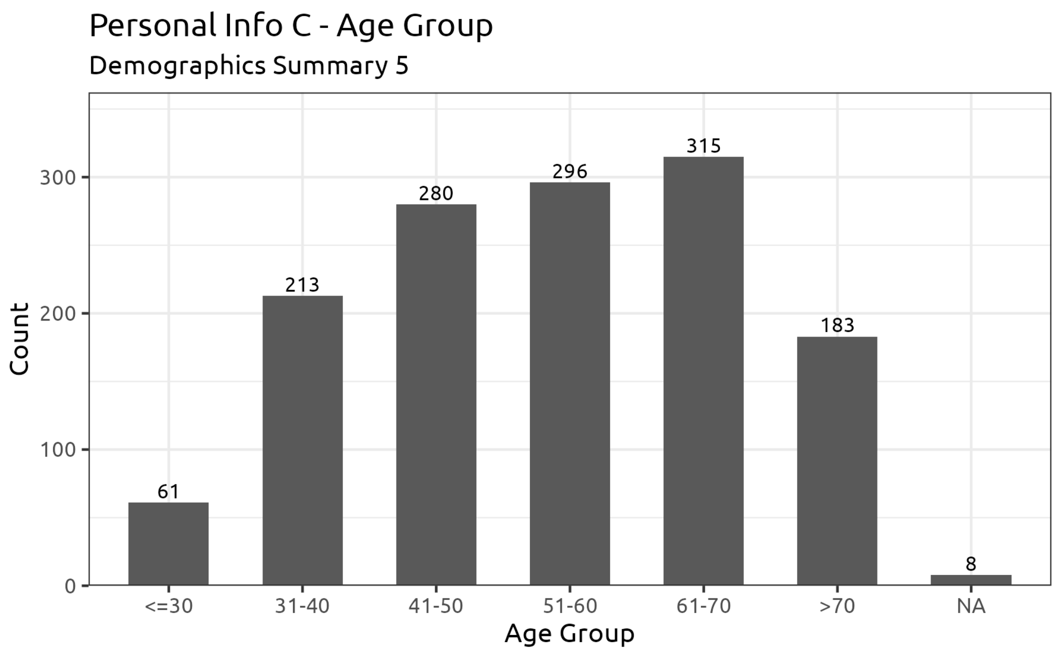

Figure A.5: Personal Info C - Age Group

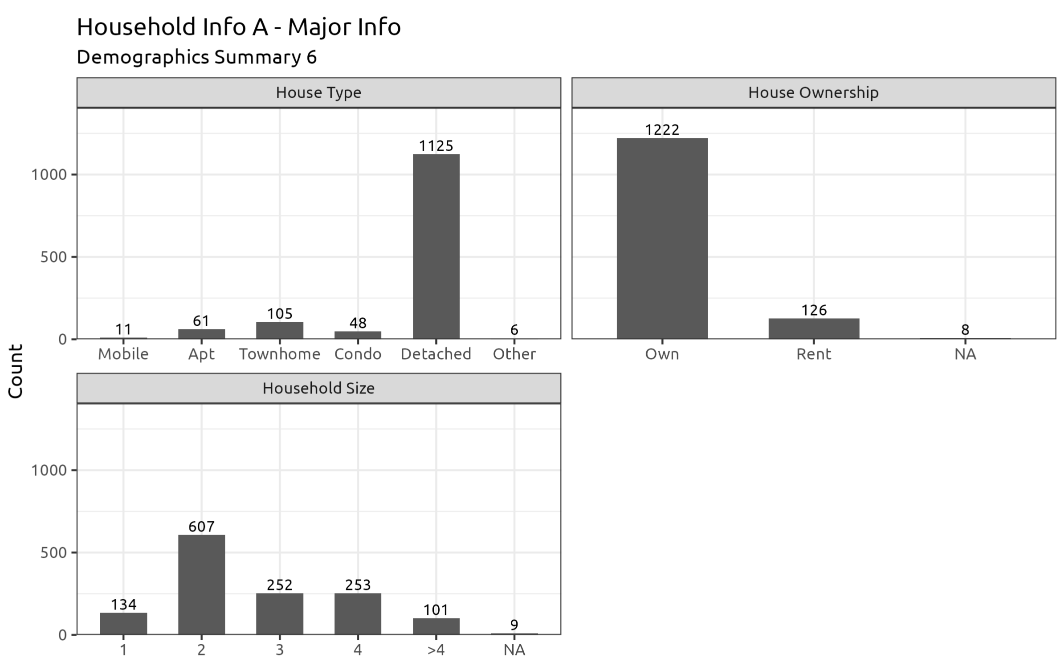

Figure A.6: Household Info A - Major Info

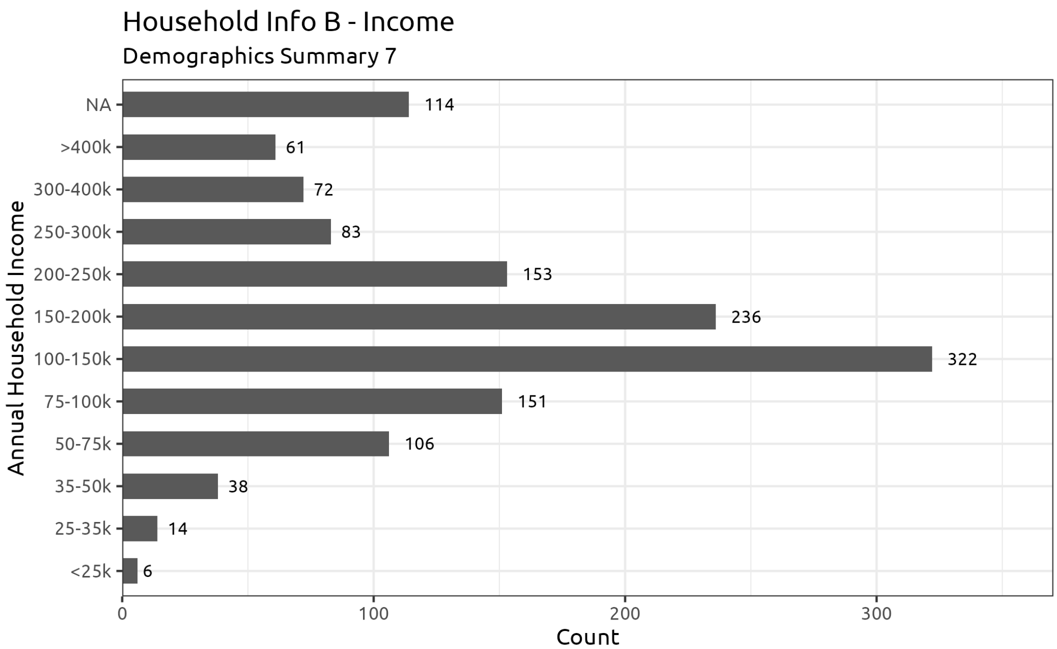

Figure A.7: Household Info B - Income

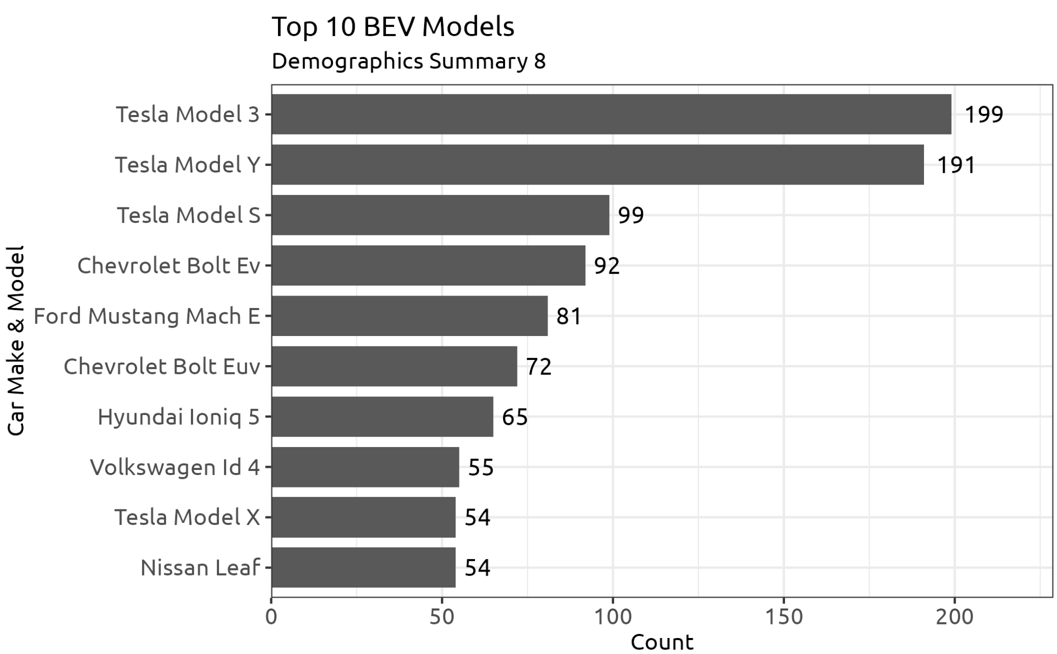

Figure A.8: Top 10 BEV Models

Table A.1: Summary of vehicle ownership characteristics in survey sample.

Category	Value	Count	Percentage
Car Number	1	371	27%
	2	736	54%
	3	181	13%
	4	51	4%
	5 or More	17	1%
BEV Ownership	Yes	1356	100%
Daily Distance	< 10	276	20%
	10-30	581	43%
	31-50	328	24%
	51-100	132	10%
	> 100	37	3%
	Don't Drive	2	0%
Neighbor Ownership	Own BEV	752	55%
	Don't Own	394	29%
	Not Sure	210	15%
Home Charge	Yes	1260	93%
	No	96	7%
Charge Management	UMC	718	53%
	SMC	91	7%
	No	547	40%
Lv2 Charger	Yes	1140	84%
	No	216	16%
Tesla Ownership	Yes	563	42%
	No	793	58%
V2G Interest	Yes	925	68%
	No	431	32%
Pay for V2G Charger	Willing to	577	43%
	Don't Want	318	23%
	Already Have	30	2%
	Did Not Report	431	32%

[1] *N = 1356.*

Table A.2: Demographic summary of survey sample.

Category	**Value**	**Count**	**Percentage**
Gender	Male	986	73%
	Female	355	26%
	Non-Binary	7	1%
	Did Not Report	8	1%
Age Group	≤ 30	61	4%
	31-40	213	16%
	41-50	280	21%
	51-60	296	22%
	61-70	315	23%
	> 70	183	13%
	Did Not Report	8	1%
Party	Democratic	778	57%
	Republican	187	14%
	Independent	330	24%
	Did Not Report	61	4%
Climate Awareness	Not	37	3%
	Somewhat	94	7%
	Neutral	65	5%
	Believe	323	24%
	Very	837	62%
Work Status	Student	14	1%
	Part-time	250	18%
	Full-time	691	51%
	Looking	22	2%
	Retired	339	25%
	Disabled	8	1%
	No Job	32	2%
Household Size	1	134	10%
	2	607	45%
	3	252	19%
	4	253	19%
	> 4	101	7%
	Did Not Report	9	1%
House Ownership	Own	1222	90%
	Rent	126	9%
	Did Not Report	8	1%

[1] *N = 1356.*

Multinomial Logit Models

Table A.3: SMC Model Coefficients

Attribute	**Coef.**	**Est.**	**SE**	**Level**	**Unit**
Enrollment Cash	β_1	0.0031	0.0002	50, 100, 200, 300	USD
Monthly Cash	β_2	0.0623	0.0027	2, 5, 10, 15, 20	USD
Override Days	β_3	0.1010	0.0118	0, 1, 3, 5	Days
Override Flag	β_4	0.3622	0.0538	Yes, No	-
Minimum Threshold	β_5	0.0037	0.0021	20, 30, 40	%
Guaranteed Threshold	β_6	0.0362	0.0021	60, 70, 80	%
No Choice	β_7	3.0026	0.1779	-	-

This model shows the utility of each attribute with 1 unit increment. E.g., enrollment cash coefficient of 0.0031 means increasing enrollment cash by $1 will increase customer utility by 0.0031.

Table A.4: V2G Model Coefficients

Attribute	**Coef.**	**Est.**	**SE**	**Level**	**Unit**
Enrollment Cash	β_1	0.0045	0.0026	50, 100, 200, 300	USD
Occurrence Cash	β_2	0.0863	0.0040	2, 5, 10, 15, 20	USD
Monthly Occurrence	β_3	0.1305	0.0217	1, 2, 3, 4	Times
Lower Threshold	β_4	0.0237	0.0030	20, 30, 40	%
Guaranteed Threshold	β_5	0.0278	0.0030	60, 70, 80	%
No Choice	β_6	2.8759	0.2647	-	-

See descriptions in Table A.3.

Study 2

This is an on-going study.

Evaluating the Cost-Effectiveness of Supplier-Managed Charging as a Peak Shaving Strategy

Project Overview

From Study 1, we learned that BEV owners have distinct preferences for different smart charging program attributes. However, the benefits of smart charging programs are limited by social, behavioral, and economic factors that are not yet well-understood. Utilities need to understand the charging preferences of PEV owners to design smart charging programs that are cost effective. This project aims to address this need by providing a new analysis framework to quantify the practical costs, benefits, and limitations of different BEV smart charging programs in different locations. This continued research will focus on addressing these two research questions:

1. What are the cost-benefit trade-offs for utilities implementing these programs?
2. How do these trade-offs vary across different locations?

We address these questions using a multi-method research approach integrating consumer choice survey data with energy system modeling to model how social, behavioral, and economic factors limit or facilitate the viability of different BEV smart charging programs. In collaboration with three regional utilities (Southern California Edison in southern California, Pacific Gas & Electric in central California, and National Grid in upstate New York and parts of New England), we will conduct comparative case studies to assess the cost-effectiveness of different smart charging programs across a wide range of heterogeneous preferences and needs. The research will result in a national dataset on PEV smart charging preferences and specific recommendations for smart charging programs, helping utilities maximize reductions in air pollution and GHG emissions under various conditions.

The overall plan is to model the costs and benefits of actually implementing smart charging programs by simulating program operations while also accounting for the costs associated with obtaining enough enrollment, leveraging our choice model from the first period to estimate costs. For now, we have implemented a model to examine "peak shaving" from an SMC program, answering the question of how much the peak electricity load could be reduced from a SMC program alone (i.e., just shifting the charging load away from the early evening peak and into the middle of the night). We aimed to obtain some initial results as a preparation for further researches to incorporate the environmental benefits of programs like SMC as well as comparisons of how results differ by location, leveraging our utility partners as a source of data and as consumers of our results.

Data Collection (Completed)

Three data sources are used in this analysis: (1) vehicle travel data from NHTS (NHTS, 2022) to simulate the charging load from a population of BEVs, (2) regional electricity consumption baselines from NREL (NREL, 2024) to represent the existing load on the grid, and (3) smart charging enrollment propensity data from our previous survey research (Hu et al., 2024) to estimate the costs of obtaining different levels of enrollment in the SMC program.

The first input to the model is having a representative sample of actual vehicle travel needs by household to simulate the associated charging load if those vehicles were electric. We use the 2022 National Household Travel Survey (NHTS) data as the input for vehicle travel patterns (NHTS, 2022). The NHTS data, organized by vehicle, provide detailed trip data for a sample day. To build a year-long set of trips for a representative population of vehicles, the following steps were taken. First, the day sets of trips were categorized by type of day (weekday or weekend), then weekday and weekend pairs were determined based on the NHTS weighting values assigned to each set of trips. For each pair, the trips are repeated for 365 days, assuming the appropriate weekday/weekend order and frequency. This 365 day trip set is then used to represent one vehicle of the vehicle population. This process is repeated to create a population of 10,000 vehicles.

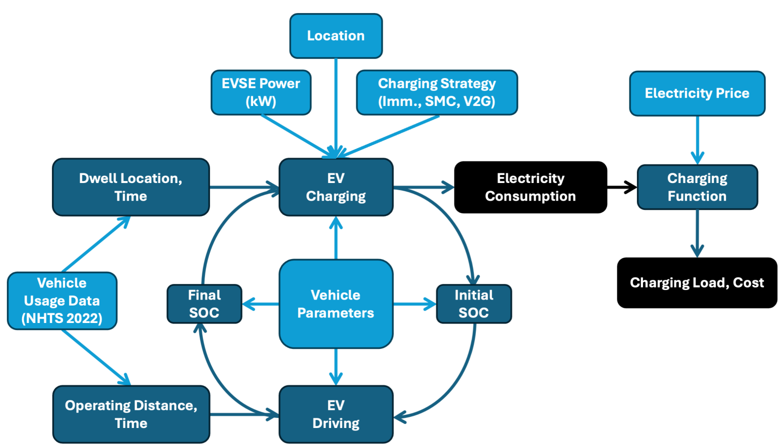

Figure 1: Flowchart of charging model logic.

Figure 1 presents an overview of the EV charging model developed. For each vehicle, we used the trip distances, travel times, dwell times, and locations to calculate (1) the change in the vehicle battery state-of-charge (SOC) throughout the day and (2) the projected electricity demand needed for the next day. From these data, the model then determines the total charging demand needed to meet the next day's demand and maintain a SOC above the specified minimum SOC. These calculations require assumptions regarding EV characteristics and charging infrastructure. We assume that the EV has a 250-mile range and an average fuel efficiency of 0.24 kWh per mile, which reflects the most common EVs on the road now in the U.S. (Gohlke et al., 2022). Further, it is assumed that the vehicle charges at home exclusively with an average charging rate of 7.2 kW up to 80% SOC when for each charging event. These values are based on available data on EVs and level 2 residential chargers and have been previously used in another recent study (Tarroja et al., 2025). The rated power of level 2 residential chargers varies between 6.6 and 12 kW, depending on the production year and charger settings, with newer chargers having a higher rated power and a configurable maximum current.

Regional electricity consumption baselines were obtained from the NREL Cambium 2024 dataset (NREL, 2024), which provides household-level electricity demand profiles for all 18 Grid Emissions Analysis (GEA) regions across the United States. These data capture seasonal variations, peak demand periods, and region-specific grid characteristics that are essential for understanding how additional EV charging load integrates with existing grid operations. The temporal resolution and geographic coverage of this dataset enables region-specific analysis of grid impacts and benefits.

Smart charging enrollment propensity was quantified through integration of consumer preference models developed from our previous survey research (Hu et al., 2024). These models characterize willingness to participate in smart charging programs as a function of monthly incentive levels, providing empirically-grounded participation rates across the full spectrum from 0% to 100% enrollment. The enrollment models account for demographic heterogeneity and regional preferences, enabling realistic simulation of program adoption under various incentive scenarios.

Simulations (Ongoing)

We have simulated the total charging load for each day over a year with 10,000 EVs charging to meet their daily needs based on the NHTS vehicle travel data. We developed baseline load curves for different GEA areas based on the NREL cambium data, then re-ran the simulation with an increasing percentage of the fleet enrolled in the SMC program, amplifying the EV numbers with respect to the household numbers of each GEA area. For EVs enrolled in SMC, we shifted the charging of those vehicle from earlier in the evening (during the typical load peak) to later into the evening and early morning to reduce the peak load. This shifting will not cause trip failure, so that if the shifting will result in SOC shortage, this EV will still apply immediate charging. This accounts for override, which will be an important indicator for our analysis. We then used our utility model from the smart charging conjoint survey results to predict the total cost to the utility of obtaining increasing levels of enrollment in the SMC program.

Regional grid integration analysis has been completed for three representative GEA regions: CAISO (California Independent System Operator), NYISO (New York Independent System Operator), and PJM East. These analyses demonstrate the methodology for combining simulated EV charging demand with region-specific electricity consumption baselines as a proof of concept for the integrated modeling approach. Expansion to the remaining 15 GEA regions is currently underway. A preliminary comparison of the outcomes of different combinations of enrollment incentives and resulting peak shaving is shown in the Preliminary Results section.

Preliminary Results

We include here some summary figures from the initial modeling work we have conducted on the cost and benefits of a SMC program for utility controlled charging. Figure 2 shows the variation of daily average grid load from 5 different shifting windows. The averaging is based on the charging behavior of all 365 days throughout a year. In each simulation, the SMC participation level was fixed as 90%, but the charging window settings for when EV charging would be delayed and when it would begin charging to avoid the peak were varied. This outcome showed us that the specific settings used in any one simulation can produce significant variation in achievable gains.

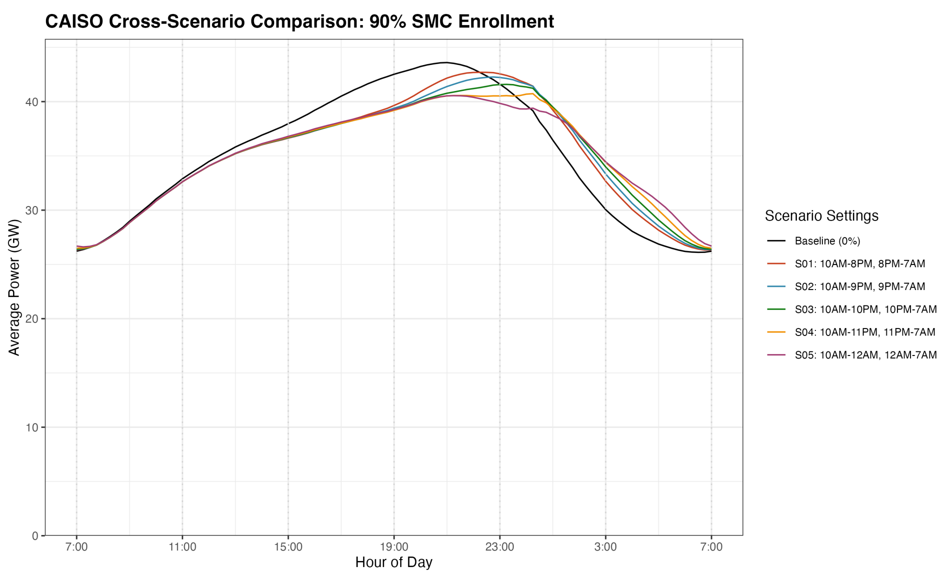

Figure 2: Peak shaving comparison for CAISO with 90% SMC enrollment under 5 scenarios. For a fixed level of enrollment in the program, the level of peak shaving achievable is highly sensitive to the time window settings used to shift EV charging into the night.

It would be clearer if we could compare the peaks of these 5 scenarios directly. Figure 3 shows the peak power comparison of the 5 scenarios from Figure 2. It is clear that scenario 5 is the best one with lowest peak power, which relocates EV charging from 10AM-12PM the current day to a valley time window of 12AM-7AM the next day.

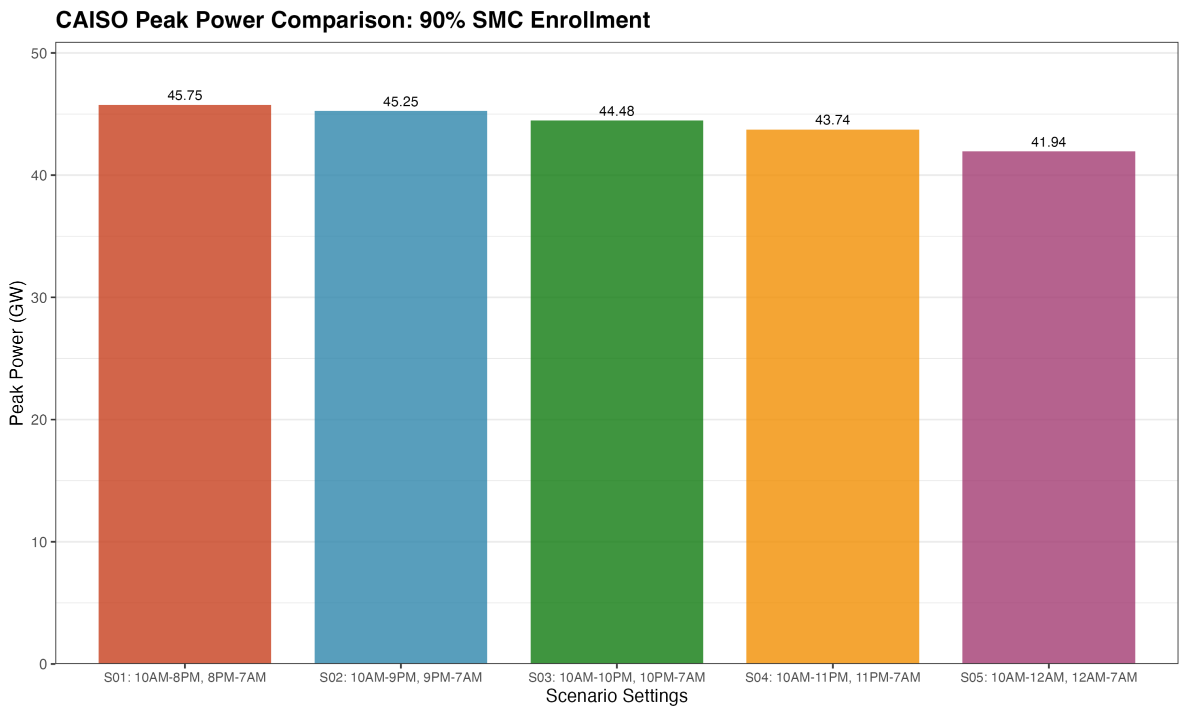

Figure 3: Single point peak comparison for CAISO with 90% SMC enrollment under 5 different shifting windows. Scenario 5 shows best peak shaving.

While Figure 2 shows results for a fixed level of enrollment in the SMC program (90% of EVs), it does not show how peak shaving evolves with increasing participation in the SMC program. To address this, we run simulations with a continuously increasing level of enrollment from 0% to 100%. Within each simulation, we explore which charging settings produce the largest reduction in peak power load, then we use the choice model from the survey to predict what cost the utility would have to incur to achieve that level of enrollment. By combining these two models, we can estimate the cost-benefit trade-off between increasing enrollment and achieving a desired level of peak shaving.

Figure 4 shows the trend of CAISO peak increase reduction while only varying one attribute of the SMC program: the monthly cash payment. It also shows the expected SMC enrollment rate associated with each level of monthly incentive (for ease of calculation, the increments are based on SMC enrollment rates of every 10%). Without any SMC enrollment, the peak load increase resulted by EV charging is 7.32 GW. As more EV owners enroll in the SMC program, the peak increase is reduced, reaching an optimal result at 3.08 GW with 90% enrollment, to achieve which the utility would need to pay around $82 per month per enrolled EV. As more EV owners enroll beyond 90%, a new peak rises in the early morning, which undermines the peak shaving.

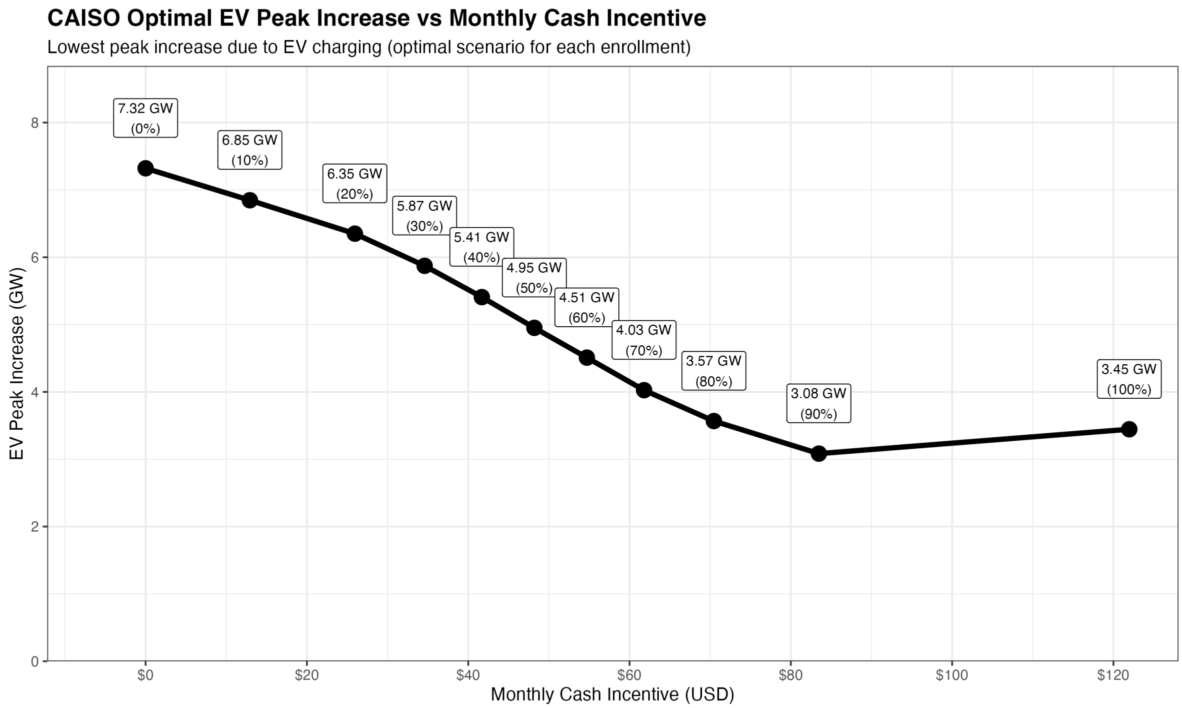

Figure 4: CAISO Cost-benefit trade off of increasing enrollment in SMC. Results suggest that monthly payments above $82 would be counter productive.

However, NYISO shows a different trend from CAISO since it doesn't create a new peak. Figure 5 shows the trend of NYISO peak increase reduction. This is close to an inverse S-shaped curve, which suggests that more monthly payment results in more peak shaving, with a diminishing return.

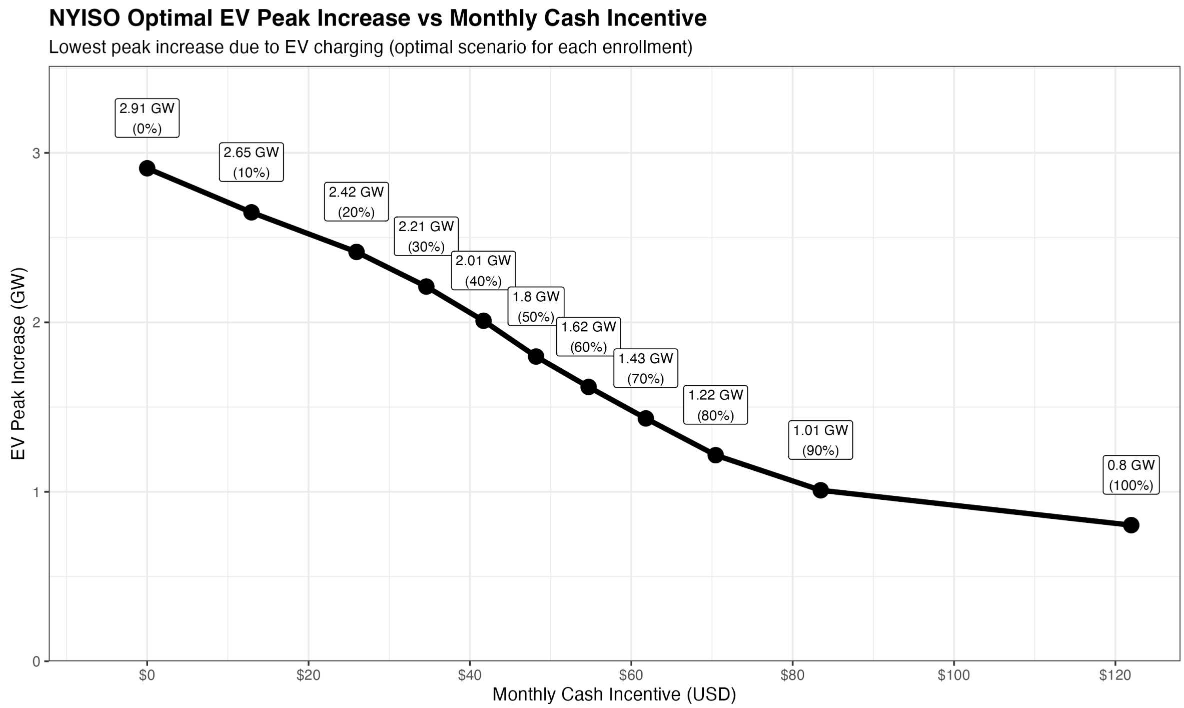

Figure 5: NYISO Cost-benefit trade off of increasing enrollment in SMC. Results suggest that more monthly payment results in more peak shaving, with a diminishing return.

Next Moves

Based on the existing 3 GEA area results, we will continue to run the same simulations for the remaining 15 GEA areas. For each area, we will combine SMC attributes including enrollment cash, monthly cash, and minimum & guaranteed battery thresholds as a portfolio, by which we can generate a more comprehensive relationship between the cost and benefits of SMC programs. With all 18 simulations, we will explore how these relationships vary by region, identifying key factors that drive differences in cost-effectiveness across locations.

Study 3

This study has been published on *PLOS One*.

surveydown: An Open-Source, Markdown-Based Platform for Programmable and Reproducible Surveys

Pingfan Hu[1]

Bogdan Bunea[1]

John Paul Helveston, Ph.D.[1*]

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[1]Department of Engineering Management & Systems Engineering, George Washington University, DC 20052, USA.

[*]Correspondence: jph@gwu.edu

Abstract

This paper introduces the surveydown survey platform. With surveydown, researchers can create surveys that are programmable and reproducible using markdown and R code, leveraging the Quarto publication system and R Shiny web framework. While most survey platforms rely on graphical interfaces or spreadsheets to define survey content, surveydown uses plain text, enabling version control and collaboration via tools like GitHub. The package renders surveys as interactive Shiny web applications, allowing for complex features like conditional skip logic, dynamic question display, and complex randomization. The package supports a diverse set of question types and formatting options and users can leverage Shiny's powerful reactive programming model to create a wide variety of interactive features. As an open-source platform, surveydown provides researchers full control over their survey implementation, including the survey application as well as where and how the resulting response data are stored. Workflows are entirely reproducible and integrate seamlessly with existing workflows for data collection and analysis in R.

Introduction

Survey research is integral to many fields, and researchers have a wide variety of software platforms to choose from depending on their needs. Those needs often extend well beyond the basic feature set of the survey software and include budgetary constraints (i.e. using a free or paid product), transparency (e.g., whether the platform is open-source), the user interface, the ability to collaborate across teams, the ability to control access to the raw data, and the learning curve associated with using the platform, among other considerations. These diverse requirements create a complex decision landscape for survey researchers seeking a software solution that meets their needs. Although there are many options to choose from, most impose fundamental limitations on reproducibility, collaboration, and integration with data analysis workflows. These limitations can impede scientific rigor, increase costs, and create barriers to effective research practices.

Existing survey platforms typically rely on graphical user interfaces (GUIs) or spreadsheets (XMLForms) to define survey content, making version control, collaboration, and reproducibility difficult or impossible. Commercial platforms often require expensive licenses, placing them out of reach for many researchers and students. Additionally, most platforms offer limited control over where and how response data is stored, raising concerns about data ownership and long-term accessibility. Finally, few platforms integrate seamlessly with modern data analysis workflows, often requiring manual data export and reformatting before analysis can begin.

This paper introduces surveydown, an open-source survey platform and software package for the R programming language (R Core Team, 2024) that addresses these limitations through several key innovations. First, surveydown employs a plain text, markdown-based system for defining surveys building on the Quarto publication system (Allaire et al., 2024), enabling complete reproducibility and version control through tools like Git. Second, surveydown allows real-time code execution during survey administration by leveraging the R Shiny web framework (Chang et al., 2024), enabling complex and highly customized surveys with features such as dynamic question generation, complex randomization, and conditional logic that few existing platforms can match. Third, while most survey platforms employ an "all-in-one" design where a single application or website is used to design the survey, field it, and store the data, surveydown embraces a disaggregated design where researchers maintain complete control over their survey implementation and data storage.

The surveydown platform is particularly valuable for researchers who need reproducible survey designs, require complex survey functionality, or want to maintain complete control over their survey data, all without needing advanced web development skills, such as knowledge of JavaScript. The platform is accessible to users with basic R knowledge, while offering advanced capabilities for those with more experience in programming or the Shiny web framework. The approach aligns with modern reproducible research practices and integrates seamlessly with R-based data analysis workflows.

The remainder of this paper details the software design (Section 2), describes its key advantages and features compared to existing platforms (Section 3), and concludes with a discussion of community adoption, future directions, and limitations (Section 4).

Software Design

Overall Architecture

The surveydown project is both an R package and survey platform that leverages three open source technologies: Quarto for survey design, Shiny for the web framework, and PostgreSQL for data storage. The `surveydown` R package provides functions and the control logic to pull these technologies together into a cohesive survey platform. Available through the Comprehensive R Archive Network (CRAN), the `surveydown` package can be installed using `install.packages("surveydown")` in the R console and is available via a MIT license. Figure 1 below is an illustration of the core technologies that form the surveydown platform.

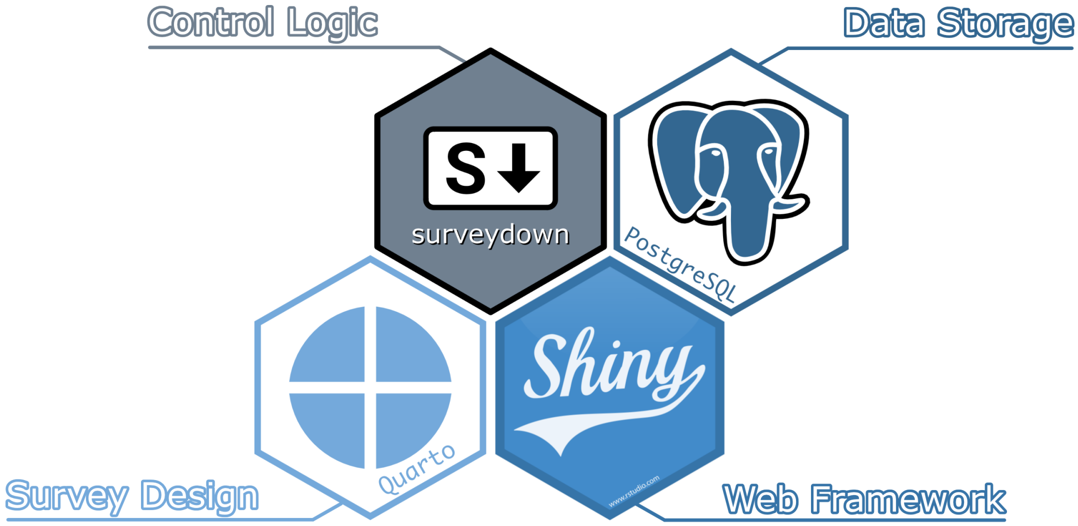


Figure 1: Core technologies in the surveydown survey platform.

Quarto for survey design, Shiny for the web framework, and PostgreSQL for data storage. The `surveydown` R package ties them together into a cohesive survey platform.

Every surveydown survey consists of a survey document and a web application, defined in two separate files named **survey.qmd** and **app.R**. These files must be in the same directory and have these precise file names as the surveydown package searches for them in the working directory. To make multiple surveys, users should organize each survey into a separate folder.

The **survey.qmd** file is a standard Quarto document. Quarto is an open-source publishing system developed by Posit PBC that enables users to combine markdown-formatted text and code chunks into single documents (.qmd files) that can be rendered into a variety of different outputs, such as html pages, pdf documents, and even presentation slides and websites (Allaire et al., 2024). With surveydown, users define all of the main survey content using plain text (markdown and code chunks) in the **survey.qmd** file, including pages, text, images, questions, and navigation buttons.

The **app.R** is a standard R script defining a Shiny web application. The `shiny` R package allows users to build interactive web applications and dashboards using only R code, enabling users to create dynamic data visualizations and web-based tools without knowing web programming languages like JavaScript (Chang et al., 2024). With surveydown, users define a Shiny application in the **app.R** file that includes global settings (libraries, database configuration, etc.) and server configuration options (e.g., conditional page skipping or question display).

The `surveydown` R package provides functions for defining survey content (e.g., survey questions, navigation buttons, etc.) as well as the overall server logic to drive the Shiny web application. Once a user is done defining the content in their survey, the Shiny application renders the **survey.qmd** Quarto document into a static html document, parses the document into survey pages, then serves each page in an interactive web application. The package also contains logic for controlling the storage of respondent data as it comes in once the survey is fielded. In the next section, we use an expositional example to showcase the construction of a minimum survey and provide a flow diagram to illustrate the overall logic flow of the surveydown platform for a typical survey.

Expositional Example

This section presents an expositional example of a two-page survey to explain the basic structure of the the **survey.qmd** and **app.R** files in a typical surveydown survey, followed by a flow diagram to explain the overall logic flows of what happens under the hood. The code below is an example **survey.qmd** file.

````
---
format: html
echo: false
warning: false
---

```{r}
library(surveydown)
```

::: {.sd_page id=welcome}

# Welcome to our survey!

```{r}
sd_question(
  type  = "mc",
  id    = "penguins",
  label = "What's your favorite penguin?",
  option = c(
    "Adélie"    = "adelie",
    "Chinstrap" = "chinstrap",
    "Gentoo"    = "gentoo"
  )
````
````

```
)

sd_next()
```

:::

::: {.sd_page id=end}

This is the last page of the survey.

```{r}
sd_close()
```

:::
```

At the top of the file is the YAML header, which defines several options to control the rendering process—namely, that the file should render into an html file (`format: html`), and that any code that is run in the file should not display the code itself or any warning messages when it runs (`echo: false` and `warning: false`). After loading the `surveydown` package, the rest of the file defines two pages: one with a multiple choice question, and another that is the ending page.

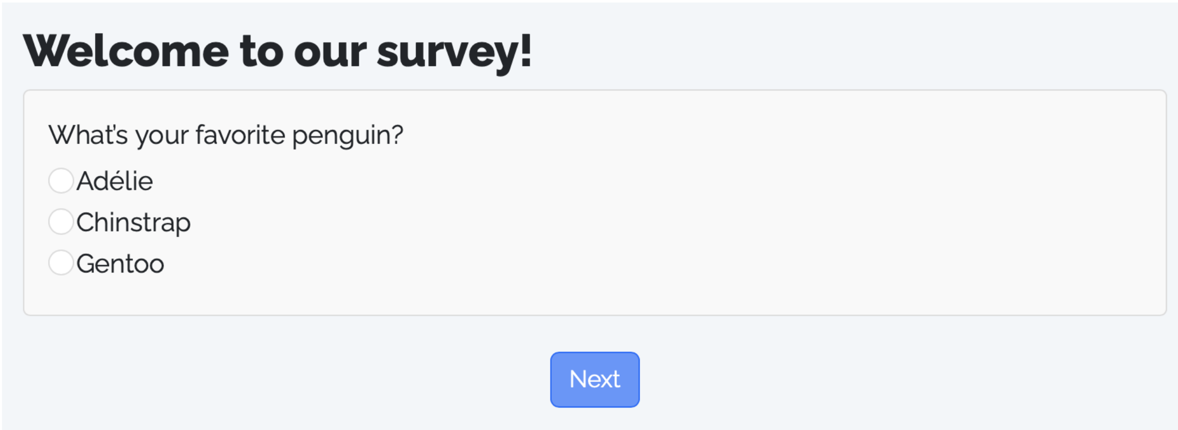
Pages are defined using three colon symbols `:::`, called a "fence", along with a `.sd_page` class definition and a page `id`. In the above example, the first page is defined as `::: {.sd_page id=welcome}`, where the `id` is set to `welcome`. In between this and the closing page `:::` symbol, users can insert content (e.g., text, images, links, etc.) using markdown formatting along with R code chunks to insert content defined using `surveydown` package functions.

Questions are defined using the `sd_question()` function. In the above example, the `type = "mc"` argument is used to define a multiple choice question. The package supports a wide variety of question types, discussed in detail later in the paper. The `id` argument is set to `"penguins"`, which is the name that will be used to store the respondent data for this question. Finally, the `option` argument defines the multiple-choice options as a named vector, where the names are what respondents see and the values are what is stored in the data. Built-in question types include:

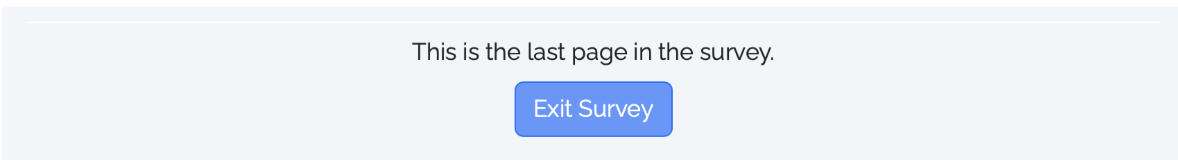
- `text`: text input type.
- `textarea`: textarea input type.
- `numeric`: numeric input type.
```

- `mc`: multiple choice type.
- `mc_buttons`: button version of `mc`.
- `mc_multiple`: multiple choice type with multiple selections.
- `mc_multiple_buttons`: button version of `mc_multiple`.
- `select`: drop down select type.
- `slider`: slider input type.
- `slider_numeric`: slider input type with numeric value, supporting single input or a range.
- `date`: date input type.
- `daterange`: daterange input type.
- `matrix`: matrix input type, containing a combination of `mc`. questions sharing a same set of options.

In addition to the question, the `sd_next()` is used inside the same code chunk to define a next button, which will by default navigate to the next page. Users can also provide an optional `next_page` argument to navigate to other survey pages if desired, using the page `id` as the `next_page` value. For now, surveydown only supports forward navigation as backwards navigation requires careful consideration of potential skipping logic that can create navigational loops, though adding support for a back button is on the development roadmap. Finally, the end page has a single sentence followed by the `sd_close()` function in another code chunk to insert a closing button that ends the survey. Figure 2 shows what the resulting two survey pages look like when rendered in a live survey app.



(a) The "Welcome to our survey!" text is in large, bold font because it is defined as a level 1 header, using the `#` symbol. The multiple choice question displayed is defined by the `sd_question()` function, and the "next" button is defined by the `sd_next()` function.



(b) The "Exit Survey" button is defined using the `sd_close()` function.

Figure 2: Screenshots of the rendered survey pages in the above example survey.

While the **survey.qmd** file defines the survey content, the **app.R** file renders the **survey.qmd** file into an interactive web application via the R `shiny` package. A minimal **app.R** file needs to contain code to 1) make the database connection to store respondent data, 2) define the user interface, 3) define the server, and 4) launch the app. The code below is an example of a minimal **app.R** file:

```
library(surveydown)

# Database Credentials (Run in R Console)
# sd_db_config()

# Connect to Database
db <- sd_db_connect()

# Define the ui (processes the survey.qmd file)
ui <- sd_ui()

# Define the server
```

```r
server <- function(input, output, session) {
  sd_server(db = db)
}

# Launch Survey
shiny::shinyApp(ui = ui, server = server)
```

After loading the `surveydown` package, the first few lines set up the database configuration. While any PostgreSQL database can be used for data storage, we recommend https://supabase.com as a free, open-source, cloud-based option. The `sd_db_config()` function can be run in the R console to store the database credentials in a local **.env** file, which include the host, port, database name, user name, password, and table name. Once the credentials are saved, the `sd_db_connect()` function is used to make a connection. In this example, the connection is created as the `db` object, which is then passed to the `sd_server()` function inside the server definition. Note that users should not store any of the credentials in the **app.R** file; rather, once the **.env** file is created, it will be used to make the database connection.

After making the database connection, the user interface (`ui`) and `server` are defined, which are required components for any Shiny application. The `ui` is created with the `sd_ui()` function, which does two things. First, it renders the **survey.qmd** file and parses it into the components needed for the survey, which are stored in a local **_survey** folder. This function only re-renders the survey content if changes to the **survey.qmd** are detected or if required components are missing. Second, it sets up a placeholder user interface to display the rendered content, which is handled in the `server()` function.

The `server()` function takes the `input`, `output`, and `session` arguments, which are standard for any Shiny application. Inside, we call the `sd_server()` function, which is the primary `surveydown` function for controlling the survey logic, such as page navigation, data handling, etc. The `sd_server()` function has many optional arguments to fine-tune the control of the survey logic, and other code can also be included inside the `server()` function for other purposes, such as setting conditions for displaying specific questions or skipping forward to other pages in the survey. Some of these options are discussed in greater detail in Section .

The final line in the file calls the `shinyApp()` function, which is the standard `shiny` package command to launch the Shiny application using the `ui` and `server` components. Users can run the application locally to test it for functionality. Once it is ready to be sent to respondents, the application can be deployed online using a variety of hosting services, such as shinyapps.io, Posit Connect Cloud, and Heroku. To deploy, using the `deployApp()` function from the `rconnect` package:

```r
rsconnect::deployApp(appName = "your_app_name")
```

Figure 3 below illustrates the overall logic flow of a typical survey using the surveydown platform, highlighting the three primary actions in the **app.R** file: connecting to a database with `sd_db_connect()`, rendering the **survey.qmd** file and creating the main UI container with `sd_ui()`, and serving the survey pages and updating the database with `sd_server()`. As the diagram illustrates, the survey designer only need to edit the **app.R** and **survey.qmd** files to define the survey content, while the `surveydown` package functions handle the survey web application implementation and database management.

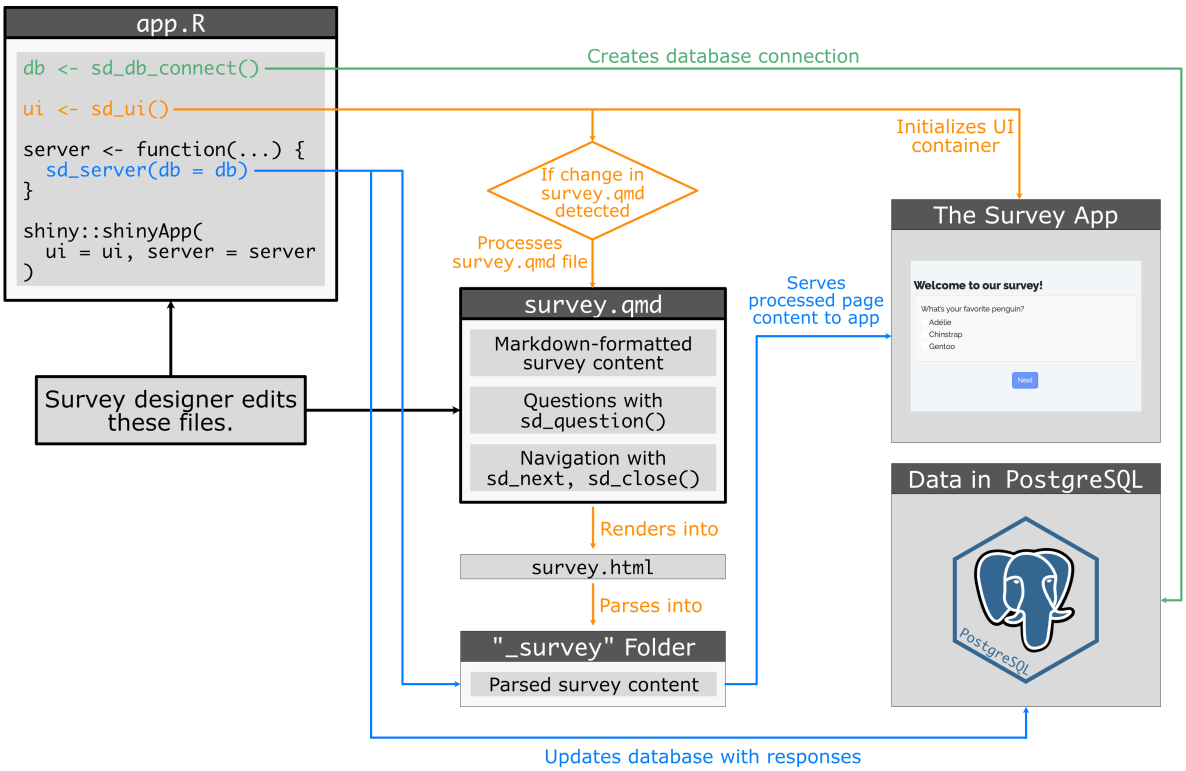


Figure 3: Logic flow diagram of the surveydown survey platform.

While this example illustrates the basic structure of a surveydown survey, the platform offers extensive functionality beyond what is shown here, including conditional display logic, page skipping based on responses, randomization of content, custom interactive elements, and robust data management features. These more advanced features, which leverage the full power of R and the Shiny framework, enable researchers to create sophisticated survey instruments that can adapt to respondent inputs in real-time.

Key Advantages and Comparison with Alternatives

The surveydown platform offers several advantages over traditional survey platforms: it is composed entirely using free and open-source software, it enables a fully reproducibility survey design experience via markdown and R code, and it offers enhanced interactivity and extensive customization via Shiny. Furthermore, its disaggregated architecture allows the researcher control over where and how the survey application and data storage are hosted, providing fine-tuned control over the overall survey implementation.

Leveraging Mature Open-Source Technologies

The selection of R, Quarto, Shiny, and PostgreSQL as the foundational technology stack for surveydown was deliberate, considering the specific needs of survey researchers and the advantages these technologies provide over alternatives.

R (R Core Team, 2024) was chosen as the primary programming language for several key reasons. First, R has an established presence in the social sciences, where much of survey research takes place. Many researchers in disciplines such as sociology, psychology, political science, and economics are already trained in R for statistical analysis, reducing the learning curve for new users and facilitating integration with existing workflows. Second, R's broader ecosystem includes extensive packages for data manipulation, visualization, and analysis, making it ideal for a platform that aims to connect survey design directly to data analysis. For the case of surveydown, R has mature integration with connecting to PostgreSQL databases. Third, R's functional programming and lazy evaluation paradigm makes the language well-suited for controlling survey operations such as randomization, question generation, and conditional logic.

Quarto (Allaire et al., 2024) was chosen as the framework for defining survey content in plain text files. As an evolution of R Markdown, Quarto combines the simplicity of markdown with deep integration of executable code. This combination is well-suited for survey contexts where textual content (instructions, questions, explanations) must be interspersed with functional components (questions, navigation, conditional elements). Quarto's ability to render content into static HTML serves as a critical intermediate step in the surveydown workflow, providing a consistent foundation for the dynamic Shiny application to build upon. Additionally, Quarto's widespread adoption in scientific publishing creates transferable skills as researchers already using Quarto for writing, presentations, or websites can apply that knowledge directly to survey design in surveydown. Finally, surveydown users will directly benefit from all future innovations and improvements to Quarto over time with limited adaptations needed in the surveydown source code.

Finally, we chose Shiny (Chang et al., 2024) as the web framework for several reasons. First, it allows for the creation of interactive web applications without requiring knowledge of JavaScript, HTML, or CSS, making sophisticated survey functionality accessible to researchers without web development expertise. Second, with over a decade of development since its initial release in 2012, Shiny has matured into a robust framework with extensive documentation, community support, and a rich ecosystem of extensions. This maturity translates into reliability and sustainability for surveydown as a platform. Third, Shiny's reactive programming model is particularly well-suited to surveys, where changes in one part of the application (e.g., a respondent selecting an answer) can trigger updates elsewhere (e.g., displaying conditional questions or updating dynamic content).

The combination of these technologies creates a synergy that would be difficult to achieve with other technology stacks. Furthermore, by leveraging open-source technologies, the surveydown project also embraces open-source. Making the `surveydown` R package open-source not only allows researchers to inspect the underlying code to understand how their surveys functions, but also allows the community of users to contribute improvements, bug fixes, and new features. As of the composition of this paper, the `surveydown` R package has reached 118 GitHub Stars, 38 addressed issues, and 52 discussions led by users with 3,703 downloads from CRAN. In addition, contributors have already added multiple features via pull requests, such as the ability to translate system messages into one of six supported languages or custom messages provided by the user. The active community provides long-term sustainability both for the surveydown project itself and for the research projects that it serves.

Reproducibility from Code

Reproducibility from code is a core advantage of the surveydown platform. The markdown-based approach to survey design is a fundamental change in thinking about how surveys can be created. Rather than using a GUI or spreadsheet interface, surveydown uses plain text files to define all survey content, enabling full reproducibility by default and easy integration with common development tools like Git for version control. By enabling a reproducible workflow for survey construction, surveys can be more easily evaluated by collaborators and reviewers, especially after data collection. For example, the entire survey instrument used in a study can be fully reproduced and experienced by other experts during a peer review process without needing proprietary software, enabling a level of transparency that is difficult or impossible to achieve with other platforms.

Alternative survey platforms do support different forms of reproducibility, but often in limited ways. For example, users of the proprietary software Qualtrics (Qualtrics, 2024) can export a **.qsf** file to share survey designs with other Qualtrics users to reproduce their surveys. However, this only enables reproducibility for users who have a Qualtrics subscription, which limits accessibility and interoperability with version control tools like Git. In contrast, by using plain text files, surveydown surveys can be easily read and directly edited without the need for proprietary software to interpret the files.

Beyond reproducibility, using plain text to define survey content has several other advantages. For example, the survey itself serves as its own documentation since code comments can be used to explain design decisions, which improves long-term maintainability. In comparison, a GUI-based application has limited ability to leave a trail of comments or suggestions about changes. In addition, surveys made using plain text can benefit from using Large Language Models (LLMs) such as ChatGPT (OpenAI, 2025) for survey design. The **survey.qmd** and **app.R** files for a survey can be provided survey to an LLM to make revisions and improvements with simple prompts. Likewise, if a user wants to implement a more complex feature than is natively supported, they can use an LLM to help solve how to implement it in Shiny. As AI tools continue to evolve, we expect AI integration with surveydown to become even more significant.

Programmable Interactivity via Shiny

Perhaps the most powerful feature of surveydown is its integration with the Shiny web framework, which enables real-time code execution during survey administration. Shiny's reactive programming framework vastly increases the capabilities of surveydown.

A common use case is *conditional control logic*, such as conditionally displaying questions and conditionally navigating to desired pages. For example, consider a multiple choice question where a respondent can select an "other" option that, if chosen, will trigger a second question to display allowing the user to specify the "other" field. This type of control to conditionally display questions is achieved using the `sd_show_if()` function in the **app.R** file, where survey designers can specify any number of conditions that, if true, will display a target question. Likewise, a designer can also conditionally skip a respondent forward to a specified page if a condition is true using the `sd_skip_forward()` function. These functions rely on Shiny's reactive programming framework where logic behavior changes depending on the actions taken by the survey respondent.

Another use case is to reactively change a question label or other text in the survey based on users' previous choices. For example, consider a question asking whether the respondent prefers *dogs* or *cats*; a natural follow-up question might be whether the respondent is a dog or cat owner. Using reactivity, the text of the second question can be dynamically updated (e.g, "do you own a *dog*" versus "do you own a *cat*") depending on what they chose on the first question. We call these "reactive questions," which are defined in the **app.R** file and called in the **survey.qmd** file using `sd_output()`.

Finally, the Shiny framework enables a wide variety of randomization options in how it handles sessions. Respondents can be assigned random values that are held constant for each user or not depending on the survey designer's objective, providing a high degree of flexibility in randomized survey designs.

Because the R Shiny framework is relatively mature, users can also take advantage of all of the existing html widgets developed to create custom questions beyond those already supported. One example of a custom question is an interactive map question using the popular `leaflet` package for creating interactive maps (Cheng et al., 2024). Users can write R code to define the map widget in the `server()` then pass it as the `output` argument in the `sd_question_custom()` function. Figure 4 below shows a screenshot of an example survey where users are asked to select the state they live in from the map.

Figure 4: Screenshot of a custom question using the `leaflet` package to display an interactive map.

Comparison with Existing Platforms

In this section we compare surveydown with other popular survey platforms along six categories:

- **User interface**: The interface used by survey designers (not participants).
- **Cost**: Whether the platform is free, paid, or has both free and paid tiers.
- **Reproducibility**: Whether a survey can be fully reproduced from source files.
- **Open-source**: Whether the platform's source code is freely available.
- **Data control**: How much control users have over survey data storage and access.
- **Programmable**: The ability to embed and execute custom code during survey runtime, enabling programmatic control over content display, data processing, and user interactions.

Table 1 compares 14 platforms across these dimensions. For the last four features, we label the feature as "Yes", "No", or "Partially", in which case "Partially" means the platform has some limited capabilities for the feature. For **Reproducibility**, we label a platform as "Partial" if surveys cannot be freely reproduced without proprietary software. For example, while Qualtrics surveys can be reproduced using .qsf files, only Qualtrics subscribers can use them. For **Data Control**, we label a service as "No" if users can only obtain access to the response data through a proprietary service, and "Partial" if the service offers the capability of storing the data on a private server, which might require a customized or more complex set of steps compared to the service storing the data.

Consider Google Forms (Google Inc., 2025), a well-known free platform with an intuitive interface for creating simple surveys. While easy to learn, it lacks reproducibility since designs cannot be captured in source files. It is not open-source, provides limited data control with data stored exclusively in Google Sheets, and offers no programmable features. In contrast, the surveydown platform distinguishes itself through its integration with the R ecosystem and Quarto publishing system. It excels in reproducibility through its markdown-based approach, provides full data control, and offers exceptional programmable features through the Shiny framework.

Most platforms in our comparison rely on graphical interfaces or spreadsheet structures (XLSForms) to define survey content, which generally limits reproducibility. Some frameworks like SurveyJS (Devsoft Baltic OÜ, 2024) and oTree (Chen et al., 2016) offer better reproducibility by storing designs as structured data files. Approximately half of the surveyed platforms are open-source, with varying degrees of cost, data control options, and programmable features. Notable open-source alternatives to surveydown include formr (Arslan et al., 2020), which also integrates with R but requires a complex server setup for self-hosting; LimeSurvey (LimeSurvey Project Team, 2023), which offers extensive features as a GUI-based platform, and Open Data Kit (Hartung et al., 2010), which excels in field-based mobile data collection but creates a disconnect between survey design and analysis environments.

Within the R ecosystem specifically, several approaches have emerged that also leverage Shiny for survey implementation. Kaufman (2020) highlighted the potential of R-based survey tools with Shiny using a series of examples, but did not provide a comprehensive package (Kaufman, 2020). A close alternative to surveydown is shinysurveys package, by Trattner and D'Agostino McGowan (2021), which offers a more formalized implementation comparable to Google Forms, and light programmability support with R code. The approach provides reproducibility but with relatively simple functionality limited to basic survey designs that rely on predefined functions and structures, offering less flexibility for complex survey designs and custom interactive elements (Trattner and D'Agostino McGowan, 2021).

Given the flexibility of the Shiny web framework, surveydown can also serve as a free and open-source alternative to existing proprietary platforms for more specialized purposes. For example, the Poll Maker by Mentimeter (Mentimeter, 2025) is a popular proprietary platform for creating interactive live polls and quizzes, where respondents see the live survey results in real time. A similar live polling capability can be achieved with surveydown using the `sd_get_data()` function, which gets the latest response data and refreshes according to a specified time interval, which can then be used to display summary results to respondents. A live-polling template is available at https://surveydown.org/templates/live_polling.

Finally, it is important to note security considerations for data collection tools like surveydown. Given surveydown's disaggregated design, three separate components require security considerations: the surveydown application code, the app hosting service, and the data storage service. For the surveydown application code, we have followed best practices in how survey response data is internally handled, such as using SQL injection prevention strategies and ensuring that users store their database credentials as a .env file to avoid accidental exposure. We also adopted an architecture where all content in the survey is served entirely from the shiny server, preventing respondents from being able to see content in the source code of other pages before getting there from the survey navigation. While the package does not yet have a security compliance certificate for the application code, this is a longer-term goal. For the app hosting service, users can choose from different providers, each of which offer different security measures. For example, while shinyapps.io is a free service, it is not HIPAA compliant. Alternatives such as Heroku or Hugging Face may offer other security measures, and users are encouraged to review their security needs before choosing a hosting service. Finally, for data storage, we suggest Supabase as a free, open-source, and convenient to use platform that has TLS encryption among other security features, including multi-factor authentication (MFA) and being SOC 2 and HIPAA compliant.

Table 1: Comparison of Features for Select Survey Platforms

Platform	User Interface	Cost	Reproducible	Open Source	Data Control	Programmable
Google Forms	GUI	Free	□	□	□	□
REDCap	GUI	Free/Paid	◪	□	■	■
Qualtrics	GUI	Paid	◪	□	□	■
Sawtooth	GUI	Paid	◪	□	◪	■
CASIC Builder	GUI	Paid	□	□	◪	□
SurveyCTO	GUI	Paid	◪	□	◪	■
QDS	GUI	Paid	□	□	□	□
LimeSurvey	GUI	Free/Paid	◪	■	□	■
Open Data Kit	XLSForms	Free/Paid	◪	■	◪	■
oTree	GUI, Python	Free/Paid	■	■	■	■
SurveyJS	GUI, JavaScript	Free/Paid	◪	■	■	■
formr	XLSForms, markdown, R	Free	◪	■	◪	■
shinysurveys	R, CSV	Free	■	■	■	◪
surveydown	markdown (Quarto), R	Free	■	■	■	■

Legend: ■ = Yes, ◪ = Partially, □ = No

Discussion and Conclusion

The surveydown platform represents a significant step forward in survey methodology by bringing the principles of reproducible research to survey design and implementation. By combining the expressiveness of markdown, the computational power of R, and the interactivity of Shiny, surveydown enables researchers to create sophisticated survey instruments that are fully documented, version-controlled, and integrated with data analysis workflows.

One of the primary contributions of surveydown is the idea of achieving full reproducibility through code. By defining surveys in plain text (markdown and R code), surveydown enables complete reproducibility and version control of survey instruments, supporting transparent research practices and long-term preservation of survey instruments. The platform also offers programmable interactivity by leveraging the Shiny web framework, enabling real-time code execution during survey administration. Another significant contribution is its open and disaggregated architecture that separates survey design, deployment, and data storage, giving researchers control over each component. Finally, as a free and open-source platform, surveydown removes financial barriers to sophisticated survey research tools while providing extensive customization options and benefiting from a growing community of contributors.

The platform does have limitations. Since the platform requires some minimal knowledge of markdown and R, it creates a higher entry barrier compared to typical GUI-based platforms, potentially limiting adoption among researchers without coding experience. Additionally, while the disaggregated architecture provides flexibility, it also requires users to handle deployment and database configuration, which may be challenging for some users, though careful documentation and tutorials helps ease these barriers. From a functionality perspective, although surveydown can currently handle complex survey designs, it does not yet match all specialized features of mature platforms, especially with respect to participant recruitment and tracking as some platforms do (e.g. Qualtrics). Finally, as with any web-based survey platform, performance under high concurrent loads depends on the hosting service chosen by the user. While free hosting options like shinyapps.io exist, users may need to pay for greater hosting server performance.

Looking forward, surveydown has several promising future directions. A graphical interface that creates the **survey.qmd** and **app.R** files for a surveydown survey would lower the entry barrier for users with limited coding experience while maintaining a reproducible workflow. This approach would bridge the gap between ease-of-use and reproducibility, potentially broadening the platform's appeal. We are in the process of building this tool as a companion package called sdstudio (https://github.com/surveydown-dev/sdstudio), which will serve as a comprehensive studio for building, previewing, and managing surveys using a GUI while maintaining full reproducibility. In addition, building a comprehensive library of templates for common survey designs would accelerate implementation for new users and promote best practices in survey design. We have already begun this with a series of existing templates available on the main documentation website at https://surveydown.org. Also, while the current implementation is responsive, developing specialized mobile question types and layouts would improve the experience for respondents on mobile devices, which represent an increasing share of survey participants.

As survey research continues to evolve, platforms that emphasize transparency, reproducibility, and programmatic flexibility will become increasingly important. The open-source nature of surveydown ensures that it can grow alongside changing methodological requirements and technological capabilities, driven by the needs of the research community it serves. By reimagining survey design through code, surveydown not only addresses practical limitations in existing platforms but also aligns survey methodology with broader trends toward computational reproducibility in scientific research. This approach has the potential to enhance the rigor, transparency, and long-term value of survey-based research across disciplines.

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