SUSTAINABLE TRANSPORTATION, SUSTAINABLE RESEARCH: CONSUMER ADOPTION AND GRID PEAK-SHAVING OF BATTERY ELECTRIC VEHICLE SMART CHARGING, INSPIRING THE SURVEYDOWN OPEN-SOURCE SURVEY PLATFORM

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Sustainable Transportation, Sustainable Research: Consumer Adoption and Grid Peak-Shaving of Battery Electric Vehicle Smart Charging, Inspiring the surveydown Open-Source Survey Platform

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Dedication

This dissertation is dedicated to my parents, Sixiang Hu (胡四祥) and Chunzhi Ping (平春芝), whose steadfast support and quiet encouragement have made the path I chose feel possible at every turn.

To my wife, Yangyang Li (李洋洋), whose companionship has carried me through every long night and uncertain day. Your presence is the most enduring source of strength in my life.

To my grandparents, who left us in 2025. Though this milestone arrived just beyond your reach, your love is with me in every step that follows.

To my friends, for the priceless friendship and support that made the difficult moments bearable and the good ones richer. I could not have arrived here without you.

And to my advisor, Dr. John Paul Helveston, whose guidance and mentorship have shaped not only this dissertation but the scholar I have become.

Acknowledgments

Dr. John Paul Helveston has been my advisor throughout my PhD. The story of how we met is a little unusual. I never reached out to him first, and I had no plan to pursue a PhD at the time. He reached out to me, saying he had a grant and was looking for a PhD student to work on smart charging for battery electric vehicles (BEVs), and that my background looked like a potential match. I thought, why not? I would not get a second chance like this. Most prospective students reach out to advisors first; it is far less common for an advisor to find a student and invite them on board. I still remember our first in-person conversation. I had parked my car and paid for one hour of parking, and we ended up talking for three full hours. He invited me to GW Coders, the data science group at George Washington University, and confirmed that I had a working foundation in data science. Although I had mainly used Python, picking up R was straightforward, and after taking his courses I became comfortable in R and in the broader data science workflow.

Those early conversations shaped the contours of this dissertation: first, smart charging adoption among BEV owners and the choice modeling used to capture owners' willingness to participate; and second, the peak-shaving benefits that follow for the grid and the simulation work that quantifies the grid-side impact. That is the high-level arc of the work that became this dissertation.

An unexpected outcome of this PhD has been the surveydown project, and the motivation was simple. Throughout our survey research we kept running into platforms that were either hard to use or required a subscription, and in many cases both. We were paying for a service that did not meet our needs. That frustration pushed us to build an open-source survey tool that other researchers, in our lab, across George Washington University, and globally, could use without the same constraints. We had the chance to present this unexpected but successful outcome to our funder, the Alfred P. Sloan Foundation, and they were enthusiastic about it.

Pursuing a PhD builds a thick and durable skill set. In my case that covers R, data science, choice modeling, and the ability to design, execute, and present a research project end to end. The start of my PhD also coincided with the start of the new AI era, and alongside my data science training I have gained substantial exposure to AI and agentic engineering. Being able to weave AI tools into a research workflow is a must-have skill in this era, and I leave my PhD confident that I have a solid data science foundation and can leverage AI on any project I take on.

Beyond the skill set, the larger takeaway from Dr. Helveston has been the mindset, and we have talked about it many times. Skills define what I am capable of doing. Mindset defines how I approach the work itself. From him, I have learned never to give up, to take ownership of every piece of work, and to see every project as part of a larger system, with its interconnections, its origins, and its consequences.

Dr. Helveston is also genuinely easy to be around. He has been as much a good friend as a good mentor, giving me wide latitude to define my own research agenda while pointing me toward sensible directions whenever I needed them. Over these four years, my wife and I have come to know him and his family well, and we are grateful for that friendship.

I met Dr. Caitlin Grady before I met Dr. Helveston; she introduced us, and I cannot thank her enough for that connection. I am equally grateful for the summer research opportunity she offered me, which was the starting point of my work in data science applied to transportation and an early seed of my interest in AI.

Dr. Johan René van Dorp, Professor and Graduate Director, gave me high-level guidance on the very first day of my enrollment that cleared up many of my uncertainties. Whenever I was unsure about my coursework or my path at George Washington, I went to talk with him, and our conversations were always clarifying. I remember telling him, on the verge of starting the PhD, that I would work very hard to earn this degree. He replied, "Yes, everyone who pursues a PhD should work hard, including you." That sentence has stayed with me, and has been a quiet source of motivation ever since. Dr. van Dorp also served as the examiner for our PhD coursework, and it is thanks to him that I gained a solid foundation in data science and statistics.

Dr. Eric Hittinger has been both a close collaborator and a good friend, owing to his full engagement with every one of my PhD projects, his patience, and his consistent availability. He encouraged me to submit to IEEE VPPC 2024, which became my first conference presentation, and his guidance in person at that event was invaluable. As an experienced researcher in sustainable transportation, he has been generous with his time on the substance of the work and on the manuscripts that grew out of it.

The collaboration team behind our BEV smart charging work includes Dr. Brian Tarroja, Dr. Matthew Dean, and Dr. Kate Forrest at UC Irvine, Dr. Eric Hittinger at the Rochester Institute of Technology, who also served on my committee, and

Dr. Alan Jenn at UC Davis. The surveydown project owes a significant debt to Bogdan Bunea, a Helveston Lab member and Computer Science undergraduate at George Washington University, whose work on the database infrastructure made the platform possible.

I have also benefited from being part of the Helveston Lab. Dr. Lujin Zhao, Dr. Leah Kaplan, Dr. Laura Roberson, Dr. Xiatian Iogansen, Zain Hoda, Bogdan Bunea, and every other member of the lab have made these years substantively richer and more enjoyable. Thank you all. More broadly, I thank the Engineering Management and Systems Engineering community at George Washington University for the feedback, conversations, and day-to-day collegiality that quietly shape a PhD.

I am grateful to my close friends Ailing Hu, Hanzhang Zhao, Yansheng Wang, Shihua Wang, Andrew Chiang, Lian Wang, Enting Liu, Yunduo Zhao, and Zihao Wang for their support throughout these years. I have enjoyed sharing ideas with each of you and learning from your experiences. I count myself lucky to have met you in my college years and to have remained close with you to this day.

Finally, I thank my wife, Yangyang Li, without whose support I would not be who I am or have accomplished what I have. I also thank my parents, Sixiang Hu and Chunzhi Ping, whose support has meant a great deal to me; I hope I have become someone you are both proud of.

This research was supported by the Alfred P. Sloan Foundation under Grant No. G-2023-20976. The views and conclusions contained in this study are mine and should not be interpreted as representing the official positions or policies of the funding agency. I thank Southern California Edison, Pacific Gas & Electric, and National Grid for insights on utility program perspectives.

I gratefully acknowledge the early adopters of surveydown for their valuable feedback and support: Reed Benkendorf, Jeffrey Girard, Will King, Stefan Munnes, Robert Kubinec, and Christian Willig.

During the preparation of this work I used the Claude Opus 4.7 large language model to improve language for clarity and no other purpose. After using this tool, I reviewed and edited the content as needed and take full responsibility for the content of the publication.

Abstract

Battery electric vehicle (BEV) adoption is a central pathway to decarbonizing transportation, but realizing its full climate benefit depends on how charging is coordinated with the electricity grid and on the methodological tools available to study consumer behavior in this transition. This dissertation addresses three connected questions through three studies. Study 1 reports a discrete choice experiment with 1,356 current BEV owners that quantifies how program design attributes shape enrollment in supplier-managed charging (SMC) and vehicle-to-grid (V2G) programs. SMC participants value operational flexibility and modest recurring payments, while V2G participants are more sensitive to monetary incentives, reflecting the more active role of bidirectional power flow. One-time enrollment cash, recurring monthly payments, and operational flexibility, such as guaranteed charging thresholds and override allowances, each contribute differently to enrollment, and we provide an interactive web tool that helps utilities and policymakers combine these levers to maximize participation under realistic budget constraints. Study 2 integrates the empirical enrollment curves from Study 1 into a scenario-based grid simulation across the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO), sweeping time-of-use load-shifting windows, BEV adoption levels, and the full 0% to 100% range of SMC participation. CAISO achieves up to 5.6 GW of peak reduction, NYISO shows more favorable per-household cost efficiency, and cost efficiency is season-invariant in CAISO but deteriorates in NYISO winters when elevated overnight load compresses the off-peak valley window. Diminishing returns to enrollment are sharp in both regions, and enrollment beyond a threshold reconstitutes a new overnight peak on approximately 15.0% of CAISO days, showing that moderate enrollment of 30% to 50%, rather than maximum participation, is the cost-effective operating target. Study 3 introduces surveydown, an open-source markdown-based R package that uses Quarto and Shiny to enable programmable, reproducible surveys with full version control and disaggregated data storage, addressing reproducibility and licensing limitations of existing platforms and making sophisticated experimental designs broadly accessible. Together, these studies translate consumer preferences into utility program design guidance, quantify the regional and seasonal limits of grid-scale peak shaving, and contribute open-source methodological infrastructure to the broader survey research community, advancing both the practical implementation of sustainable transportation and the rigor of the research that supports it.

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Chapter 1: Introduction to Consumer Adoption and Grid Peak-Shaving of BEV Smart Charging, and the surveydown Open-Source Survey Platform

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 evaluates the peak-shaving potential and cost efficiency of supplier-managed charging programs when realistic enrollment costs and participation rates are considered. We integrate the empirical consumer enrollment curves from the first study into a scenario-based grid simulation for two contrasting U.S. regions, the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO), sweeping across time-of-use load-shifting window configurations and the full 0% – 100% range of SMC participation. The analysis reveals that CAISO achieves larger absolute peak reductions (up to 5.6 GW) while NYISO shows more favorable per-household cost efficiency; cost efficiency is season-invariant in CAISO but deteriorates in NYISO winters when elevated overnight load compresses the off-peak valley window. Diminishing returns to enrollment are sharp in both regions, and enrollment beyond a certain threshold reconstitutes a new overnight peak on approximately 15.0% of CAISO days, demonstrating that moderate enrollment, not maximum participation, is the cost-effective operating target. The findings provide region-specific guidance for utilities designing economically viable smart charging programs that balance grid benefits with program costs.

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 do the peak-shaving potential and cost efficiency 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.

1.1 Background

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 representative study in California indicates that BEVs 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 evaluate the peak-shaving potential and cost efficiency 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.

1.2 Consumer Preferences for 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 & 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.

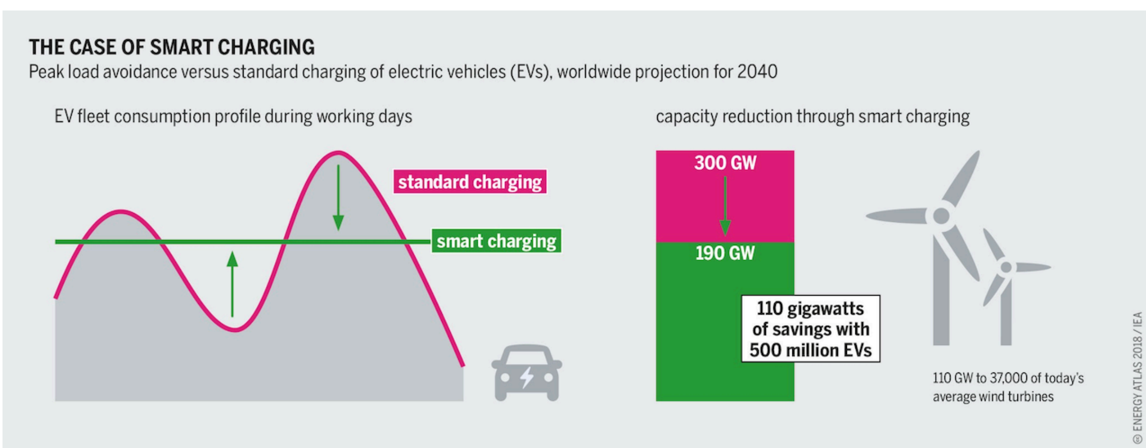


Figure 1: Smart charging helps avoid peak load (Bartz & Stockmar, 2025).

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 & 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.

1.3 Peak Shaving and Cost Efficiency of Supplier-Managed Charging

Smart charging programs represent a critical demand response strategy for managing the grid impacts of large-scale battery 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 (Coignard et al., 2018; Tarroja et al., 2015), 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 & Axsen, 2015).

This study addresses these limitations through a scenario-based regional cost-efficiency framework that integrates the empirical consumer enrollment curves generated in Chapter 2 with a grid simulation focused on two contrasting U.S. regions: the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO). The analysis draws on four empirical data sources: the 2022 National Household Travel Survey (NHTS) for vehicle travel patterns, 2025 GridStatus.io net load time series for regional grid baselines, 2025 U.S. Census detached single-family household counts to scale per-vehicle results to regional fleet sizes, and the discrete choice model from Chapter 2 that translates monthly incentive payments into participation rates.

The simulation re-assigns BEV charging from a *normal* window in the evening to a *valley* window in the overnight hours, subject to state-of-charge and travel-need protections, and sweeps across five time-of-use load-shifting window configurations and the full 0% – 100% range of SMC participation. At full enrollment, SMC shaves CAISO's evening peak by 3.7 GW (12.1%) on an annual-average day and up to 5.6 GW on the most favorable day, while NYISO sees a 1.6 GW (7.5%) reduction on the annual average. Figure 2 illustrates the resulting daily load profile shift for the CAISO grid before and after SMC enrollment.

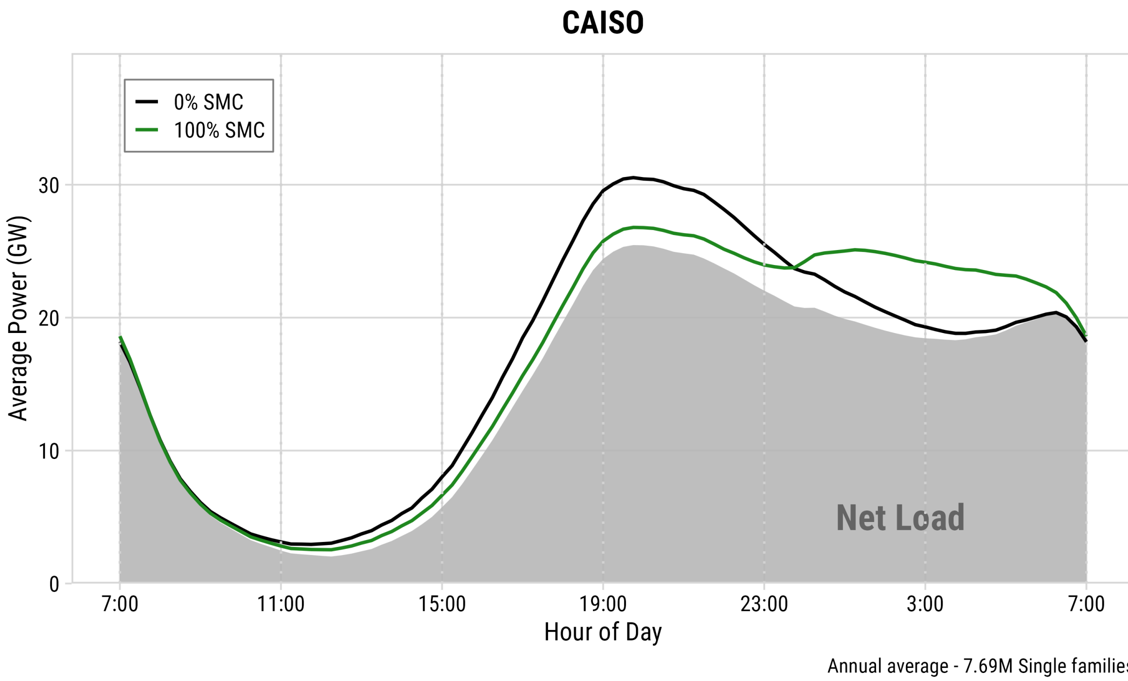


Figure 2: Daily load profiles of the CAISO grid at 0% and 100% SMC enrollment. Without SMC, BEV charging load stacks on top of the existing evening peak; under full SMC enrollment, charging is shifted to the overnight valley and the evening peak is shaved.

Cost efficiency, defined as peak reduction per dollar of monthly incentive expenditure, exhibits sharp diminishing returns in both regions: moderate participation in the 30% – 50% range captures most of the achievable peak reduction at a fraction of the cost of near-full enrollment, and on approximately 15.0% of CAISO days, enrollment beyond a certain threshold reconstitutes a new overnight peak from concentrated valley-period charging. Figure 3 shows the cost-efficiency frontier for the CAISO grid.

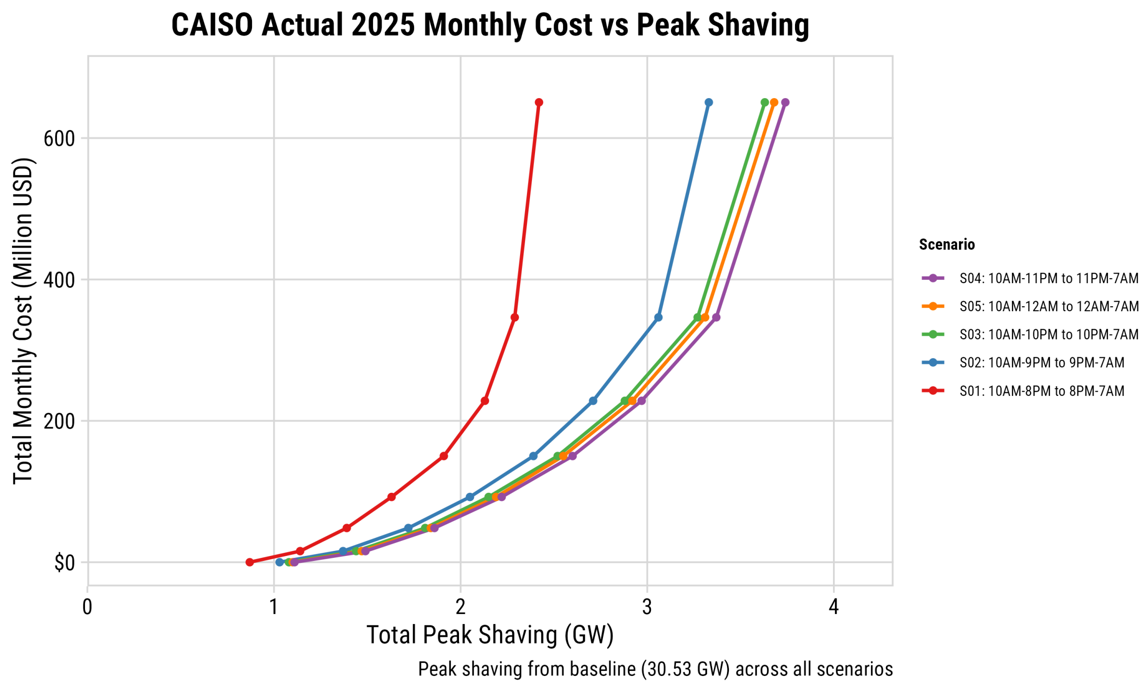


Figure 3: Cost-efficiency frontier for the CAISO grid in 2025, plotting total monthly program cost against total peak shaving across SMC enrollment levels under five time-of-use load-shifting window scenarios (S01 – S05), where the charging valley window extends progressively later into the evening.

The two regions also display contrasting seasonal patterns: cost efficiency is essentially season-invariant in CAISO, where the solar-shaped load profile keeps the gap between evening peak and overnight valley wide year-round, but deteriorates in NYISO winters when space-heating demand keeps overnight load elevated and compresses the off-peak valley window. Together, these findings demonstrate that moderate enrollment, not maximum participation, is the cost-effective operating target, and they provide region-specific guidance for utilities designing economically viable SMC programs that balance grid benefits with program costs.

1.4 Methodological Innovation in Survey Research

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.

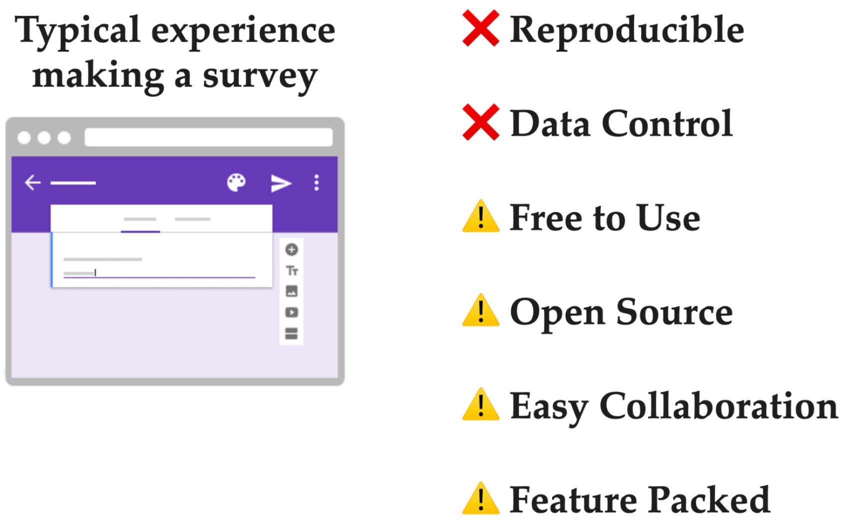


Figure 4: Limitations of typical survey platforms.

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.

1.5 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. **Peak-Shaving and Cost Efficiency Evaluation**: Existing research typically presents optimistic assessments of grid-integration benefits without adequately accounting for implementation costs and participation constraints. The second study evaluates the peak-shaving potential and cost efficiency of SMC programs under realistic conditions, integrating empirical enrollment curves with grid simulation across contrasting regional contexts.
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 BEV 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 peak-shaving and cost efficiency of SMC programs is a further exploration of this field: even though the BEV owners are willing to participate, the effectiveness of SMC should still be quantified and evaluated to prove its sustainability. This study converges two impacts from the SMC programs: 1) the peak load caused by unmanaged BEV 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 policy-makers 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 BEV 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 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.

Chapter 2: Measuring Battery Electric Vehicle Owners' Willingness to Participate in Smart Charging Programs

Note: This chapter is based on a paper published in *Environmental Research Letters* (ERL) (Hu et al., 2025a).

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 & 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 et al., 2015; Tarroja & Hittinger, 2021).

The success of these grid-integration strategies fundamentally depends on BEV owners' willingness to participate in smart charging programs. Previous research suggests that most owners are reluctant to enroll without adequate incentives, citing concerns about operational limitations and insufficient compensation (Bailey & 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 & 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 & 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 & 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 (Kubli, 2022; Lavieri & Oliveira, 2023; Parsons et al., 2014; Wong et al., 2023).

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

Our study addresses these limitations by focusing exclusively on current BEV owners with a larger sample size (N = 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.

2.1 Methods

2.1.1 Survey Design and Conjoint Experiment

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 (Eendebak & Schoen, 2017; Goos & Jones, 2011; Walker et al., 2018), a purely random design was chosen to enable identification of potential interaction effects and provide greater coverage across all combinations of attribute levels. Respondents were asked six consecutive choice questions for SMC programs, then six additional choice questions for V2G programs. Each choice question included two smart charging options and a "not interested" option, consistent with the voluntary nature of real smart charging programs.

We selected 5 attributes each for SMC and V2G programs based on reviewing prior literature, existing utility programs, and interviews with 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 is shown in Table 1 and Table 2, and Figure 5 and Figure 6 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 & 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 Table 1.

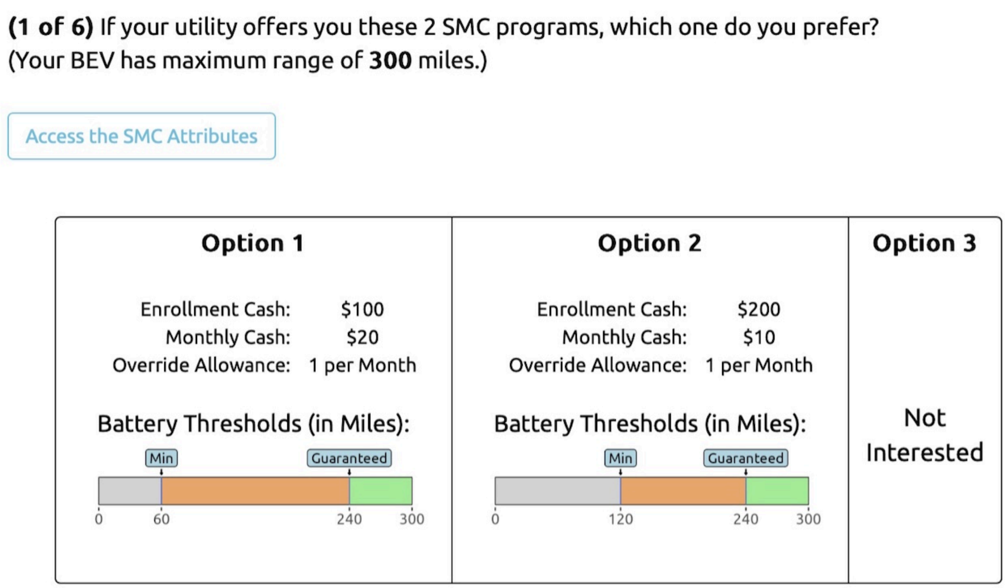


Figure 5: **Sample SMC Conjoint Question.** Each respondent was asked 6 SMC choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

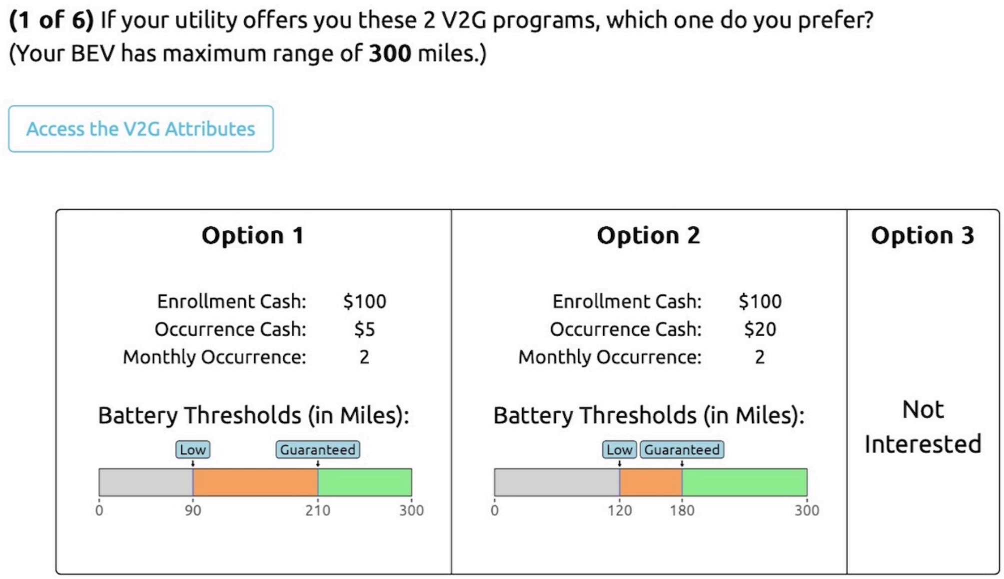


Figure 6: **Sample V2G Conjoint Question.** Each respondent was asked 6 V2G choice questions with randomized attribute values. The BEV range in the main question is dynamically defined based on the BEV the respondent claimed to own.

2.1.2 Data Collection

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 & 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 are provided in Appendix A.

2.1.3 Model Estimation

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:

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

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 Appendix A.

2.2 Results

2.2.1 Sample Characteristics and Enrollment Sensitivities

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 Appendix A.

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 7 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% confidence 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.

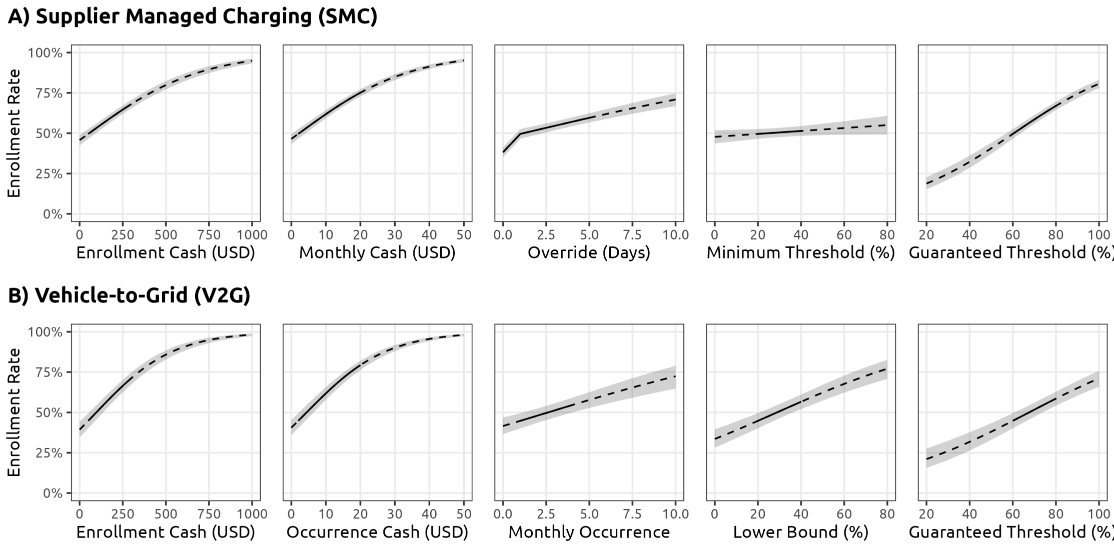


Figure 7: **Plots of smart charging program enrollment sensitivity to changes in program attributes.** Solid lines indicate predictions within the ranges of attributes included in our survey, and dashed lines indicate extrapolations beyond the range of levels shown in the survey. Gray bands reflect 95% confidence intervals based on parameter uncertainty.

2.2.2 Attribute Equivalencies

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 & Zhang, 2024; Perger & 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.

2.2.3 Scenario Analyses

Program administrators ultimately need to choose combinations of attributes when establishing programs. We conducted scenario analyses comparing specific smart charging programs against the no-choice option, developing scenarios across three categories based on prior research (Geske & Schumann, 2018; Huang et al., 2021; Wong et al., 2023): 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 8 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.

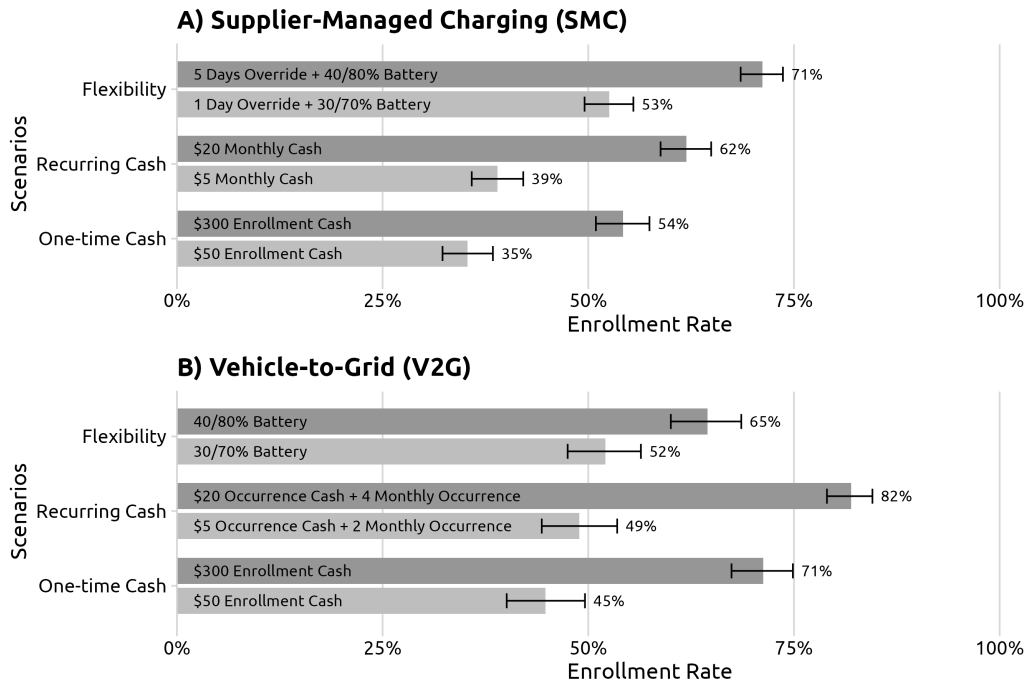


Figure 8: **Scenario analyses of SMC and V2G programs.** For both programs, we simulated three scenarios focusing on flexibility, recurring cash, and one-time cash incentives. Each scenario includes both high and low cases.

2.3 Discussion and Conclusion

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 & Zhang, 2024; Perger & 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 & Davis, 2016; Guo & 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.

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.

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

Chapter 3: Quantifying the Peak-Shaving Potential and Cost Efficiency of Battery Electric Vehicle Supplier-Managed Charging

Note: This chapter is based on a paper currently under review at *Environmental Research: Infrastructure and Sustainability*

Transportation electrification is a critical pathway toward decarbonizing the energy system and reducing greenhouse gas emissions from the transportation sector (Elgowainy et al., 2018; Jenkins et al., 2021; Shukla et al., 2022). Battery electric vehicles (BEVs) can significantly reduce lifecycle emissions compared to conventional vehicles, with reductions of up to 59% per vehicle when charged with grid electricity (Santero et al., 2026). However, these environmental benefits are contingent on both the emissions intensity of electricity generation and the timing of vehicle charging (McLaren et al., 2016).

Uncoordinated BEV charging presents substantial challenges for power system operations. Research demonstrates that unmanaged charging typically coincides with existing evening peak electricity demand periods, exacerbating grid stress, increasing infrastructure costs, and potentially elevating emissions when fossil fuel peaking generators are dispatched to meet demand (Muratori, 2018; Tarroja et al., 2015; Zhang et al., 2020). As BEV adoption continues its projected growth toward millions of annual sales in the coming decade, the impacts of unmanaged charging will intensify, potentially requiring costly grid infrastructure upgrades and generation capacity additions (Jenn & Highleyman, 2022; Weyl, 2026).

Supplier-managed charging (SMC) strategies offer a promising approach to mitigate these challenges by transforming BEVs from passive loads into flexible grid resources (Forrest et al., 2016; Xu et al., 2025). In SMC programs, utilities remotely manage charging timing and duration while ensuring vehicles reach desired charge levels by specified times (Dean & Kockelman, 2024a). By shifting charging load from peak periods to off-peak hours with lower demand and higher renewable energy availability, SMC programs can reduce peak demand, defer infrastructure investments, and improve renewable energy integration (Birk Jones et al., 2022; Coignard et al., 2018; Tarroja et al., 2015). Critically, this load shifting can also serve as a mechanism behind lower off-peak electricity rates for some consumers who participate, creating a financial incentive that aligns consumer and grid interests. As BEV fleets continue to grow, SMC may transition from a voluntary demand response option to a structural necessity, since the alternative (unmanaged charging by millions of vehicles arriving home simultaneously in the evening) would impose peak loads that many grids cannot absorb without significant and costly capacity expansion.

Despite the demonstrated technical potential of supplier-managed charging (SMC), a critical gap exists between theoretical analyses and practical implementation. Most existing studies assume optimal or near-complete participation rates and minimal implementation costs (Coignard et al., 2018; Tarroja et al., 2015), potentially creating unrealistic expectations about achievable grid benefits. In reality, SMC program success depends fundamentally on consumer willingness to participate, which varies with program attributes such as monetary incentives, operational flexibility, and battery charge guarantees (Bailey & Axsen, 2015; Sovacool et al., 2018). Furthermore, achieving meaningful enrollment levels requires incentives that utilities must provide to consumers, representing a significant program cost that affects economic viability (Bailey et al., 2023; Wong et al., 2023).

Recent empirical research has begun to quantify consumer preferences for participating in SMC programs. Studies using discrete choice experiments have revealed that consumer participation decisions are influenced by multiple factors such as monetary incentives, guaranteed charging levels, override flexibility, and other possible program design features (Huang et al., 2021; Philip & Whitehead, 2024; Wong et al., 2023). Importantly, these studies find that a non-trivial share of BEV owners express willingness to enroll even without financial incentives, suggesting an existing baseline of acceptance that programs can build on. However, these insights have not been systematically integrated into grid-scale cost efficiency analyses that account for realistic enrollment costs and participation constraints.

The choice of region also shapes SMC outcomes, yet few studies have compared cost efficiency across different grid contexts. We focus on the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO) because they represent a sharp structural contrast: both rank among the leading states in BEV adoption, but differ in their generation mixes, load profiles, and climate. CAISO is dominated by solar production during the day, producing a steep evening net load ramp (the so-called "duck curve") that makes charging timing critical. NYISO relies more on dispatchable hydropower, yielding a flatter net load profile. Furthermore, California's warm summers drive cooling-dominated peaks, while New York's cold winters create a distinct heating-season demand pattern. Together, these contrasts make CAISO and NYISO a well-matched pair for understanding how grid context shapes SMC program performance.

This study addresses current research gaps through a scenario-based simulation of SMC programs, sweeping across utility-defined time-of-use (TOU) load-shifting window configurations and SMC participation levels to quantify peak-shaving potential, and integrating empirical consumer enrollment modeling to evaluate program cost efficiency in CAISO and NYISO. Figure 9 in Section 3.1.1 outlines the two-stage analytical workflow. The peak-shaving model includes thousands of scenario combinations to generate net load profiles with and without SMC participation, and the cost-efficiency simulation joins the best-performing outcomes with consumer enrollment curves to compare program costs against achieved peak demand reduction for both regions (see Section 3.1 for more detail).

Our approach makes several key contributions to the literature. First, we integrate empirical consumer preference data from a discrete choice experiment with 1,356 BEV owners directly into a grid simulation, providing cost-benefit assessments that account for the cost of consumer enrollment instead of assuming arbitrary participation rates. Building on this foundation, we conduct regional analyses in two representative states (California and New York), revealing how SMC cost efficiency varies with regional grid characteristics and providing actionable insights for utility program design in different market contexts.

Moreover, we demonstrate that optimal enrollment levels are often well below 100% due to diminishing returns and the potential for creating new peak demand periods when excessive charging is shifted to off-peak hours, which has important implications for program design and utility planning. Additionally, we examine multiple time-of-use pricing window configurations, showing that program design choices regarding when to restrict and allow charging significantly affect peak-shaving performance and providing guidance for optimizing SMC program parameters.

3.1 Methods

We evaluate the peak-shaving potential of supplier-managed charging (SMC) programs in two representative U.S. grid regions, CAISO (California, 7.69 million detached single-family households) and NYISO (New York, 3.16 million), which differ sharply in generation mix and climate (Bureau, 2025). The analysis is scoped to residential Level 2 charging in detached single-family homes, the housing type most likely to have access to home charging and to be eligible for SMC programs. All simulations fix a 1:1 BEV-to-household ratio as the baseline adoption assumption, representing full BEV ownership among detached single-family households. While this does not represent a current BEV adoption scenario, we chose this ratio because it reflects a near upper bound of BEV adoption within each area, and because concurrent BEV charging during peak periods is less problematic at lower adoption levels.

The simulation sweeps across two sensitivity axes. The primary axis is SMC participation, simulated across the full 0% – 100% enrollment range in 10% steps. The secondary axis is the TOU load-shifting window: in each of five configurations, charging is unrestricted from 7 AM to 10 AM, delayed from 10 AM until the off-peak window begins, and delivered at maximum rate during the off-peak window until 7 AM, with the configurations differing only in when the off-peak window starts, stepping from 8 PM to 12 AM in one-hour increments. The 11 PM start yields the best peak-shaving performance across both regions and is used for all reported results. Each scenario is in turn evaluated under three temporal conditions that each target a different focus for peak reduction: annual average daily profiles, extreme peak-shaving days, and seasonal averages. For every condition, cost efficiency is obtained by combining the consumer enrollment model with the grid simulation results to express program cost per GW of peak reduction.

3.1.1 Workflow Overview

The framework proceeds in two sequential stages shown in Figure 9. The first stage is the peak-shaving model. Three data sources enter the simulation: 2022 NHTS vehicle trip records, which define travel timing and distances; 2025 GridStatus.io net load time series for CAISO and NYISO, which provide regional grid baselines; and 2025 U.S. Census detached single-family household counts, which scale per-vehicle results to regional fleet sizes. The model is run across five TOU window configurations, three BEV adoption rates, multiple date ranges, and eleven SMC enrollment levels from 0% to 100%, generating thousands of net load profiles that show grid demand with and without SMC participation across every scenario combination. Cross-scenario comparisons then identify the best-performing TOU configuration, whose outputs are passed to the second stage.

The second stage is the cost efficiency simulation. The selected peak-shaving outcomes are combined with a fourth data source: consumer enrollment curves estimated from a discrete choice experiment with 1,356 BEV owners (Hu et al., 2025a), which translate monthly incentive payments into participation rates. For each enrollment level, the corresponding per-household incentive is multiplied by the number of enrolled households to yield the total monthly program cost. The resulting efficiency frontiers compare achieved peak shaving against program expenditure across both regions, all seasons, and multiple adoption scenarios.

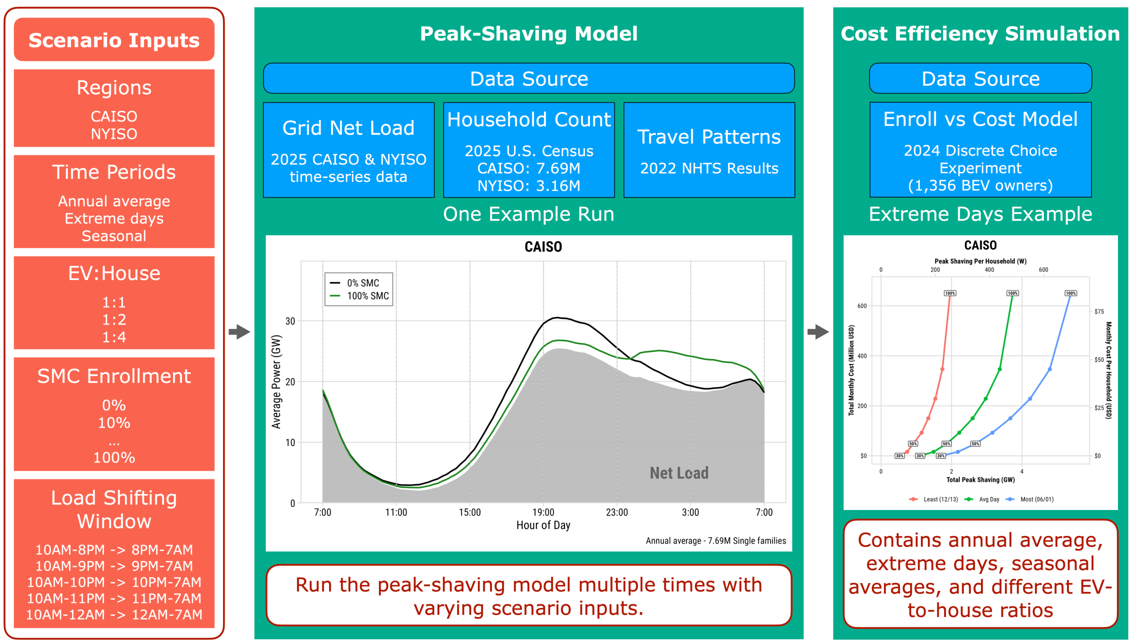


Figure 9: **Two-stage simulation workflow for SMC peak-shaving and cost efficiency analysis.** Three empirical data sources feed the peak-shaving model, which sweeps across scenario combinations to generate net load profiles with and without SMC participation. The best-performing outcomes enter the cost-efficiency simulation, where consumer enrollment curves from a discrete choice experiment with 1,356 BEV owners translate enrollment levels into program costs to produce efficiency frontiers for CAISO and NYISO.

3.1.2 Data Preparation

Four empirical data sources underpin the scenario-based simulation. The 2025 U.S. Census provides detached single-family household counts, which set regional fleet sizes at the 1:1 BEV-to-household adoption assumption (Bureau, 2025). The 2022 NHTS supplies vehicle trip records, which determine charging timing and energy needs (NHTS, 2022). GridStatus.io historical net load time series for CAISO and NYISO constitute the regional grid baselines (Grid Status, 2026a; 2026b). Consumer enrollment curves from a discrete choice experiment with 1,356 BEV owners translate monthly incentive payments into participation rates for cost efficiency analysis (Hu et al., 2025a).

The 2025 U.S. Census (Bureau, 2025) data is a comprehensive collection of demographic information. For our study, the relevant data are the number of detached single-family households in each Generation and Emissions Assessment (GEA) region, as defined by the NREL Cambium dataset. This household type is chosen primarily because it represents the majority of all housing units. For example, California ISO (CAISO) has about 9.07 million households in total, among which 7.69 million (85.0%) are detached single-family households. Furthermore, detached single-family households are more likely to have access to residential Level 2 charging infrastructure, which is the focus of this study. This is also reflected by the demographic results in our BEV owner SMC preference survey (Hu et al., 2025a), where 1,125 out of 1,356 respondents (83.0%) live in detached single-family homes.

The 2022 NHTS (NHTS, 2022) data provides realistic vehicle trip patterns across the U.S. with specific weekdays and time intervals. Raw records are filtered to retain only personal-vehicle trips, excluding public transit and other travel modes. Trips exceeding 200 miles are removed to reflect the assumed BEV range, and trips with vehicle speeds above 90 mph or implausible values are discarded as data errors. After cleaning and filtering, the dataset retains over 26,000 trips. These trips are not necessarily from BEV owners, but represent general travel behavior. We assume that there is no significant behavioral difference between BEV and non-BEV owners in terms of trip timing and distance, and that in between the trips, vehicles are parked at home with charging availability. We simulated 10,000 vehicles with year-long travel patterns constructed by repeating NHTS weekday/weekend trip sets while maintaining sampling weights. Multipliers are applied on the results to scale up to grid-level impacts based on Census household counts and BEV adoption scenarios. For example, in CAISO, with 7.69 million detached single-family households, there are 7.69 million BEVs in total (assuming 1:1 BEV-to-household ratio). Thus, each simulated vehicle represents 769 (7.69 million / 10,000) vehicles in the scaled results.

The standardized data of CAISO (Grid Status, 2026a) and NYISO (Grid Status, 2026b) provide historical electricity supply for California ISO and New York ISO at 5-minute resolution categorized into different load types. After data cleaning, we obtained historical base load data for these two regions at 15-minute resolution, treated as *net load*. We collected full data for the years 2024 and 2025, and used

2025 as the representative data source because it provides the most recent complete year of grid supply history. The 2024 results are presented in Appendix B as supplementary material, aligning with the BEV owner preference data collected in 2024 in our previous study (Hu et al., 2025a). The net load represents the grid electricity supply excluding variable sources (like PV, solar, and wind power). In a single scenario, the BEV charging load is stacked on top of the net load to evaluate the overall peak demand impact, while the peak reduction is only applied on the BEV charging load.

As a supplementary grid baseline, we also collected and cleaned the Cambium 2024 Mid-case hourly data by GEA regions from the National Laboratory of the Rockies (NLR), selecting CAISO and NYISO from the 18 available GEA regions as projected grid baselines (NREL, 2024). The NLR results are shown in Appendix B as supportive material.

To estimate the cost of enrollment, consumer enrollment modeling draws on results from a discrete choice experiment with 1,356 BEV owners conducted in 2024 (Hu et al., 2025a). The survey is nationwide and can be applied to any of the 18 GEA regions. The experiment presented respondents with hypothetical SMC program options varying in monetary incentives (monthly payments), operational flexibility (override frequency), and battery charge guarantees (thresholds). Using a mixed logit model, we estimated the influence of these attributes on participation probabilities. For this study, we focus on the recurring monetary incentive attribute while holding non-monetary attributes constant (override = 0/month, thresholds = 0%/40%) to isolate the effect of monthly payments on enrollment rates.

Figure 10 shows the predicted enrollment rate as a function of monthly incentive payment, derived from this mixed logit model. At zero incentive, approximately 30.0% of BEV owners would participate voluntarily. The solid portion of the curve spans the \$2 – \$20 monthly incentive range directly covered by the survey; a \$20 payment raises predicted enrollment to approximately 60.0%. The dashed extension extrapolates model predictions to higher incentive levels, with the shaded band showing the 95% confidence interval around all estimates. The curve is concave throughout: each additional dollar of incentive yields a progressively smaller marginal enrollment gain, and reaching 100% enrollment requires a monthly payment of \$85 per household.

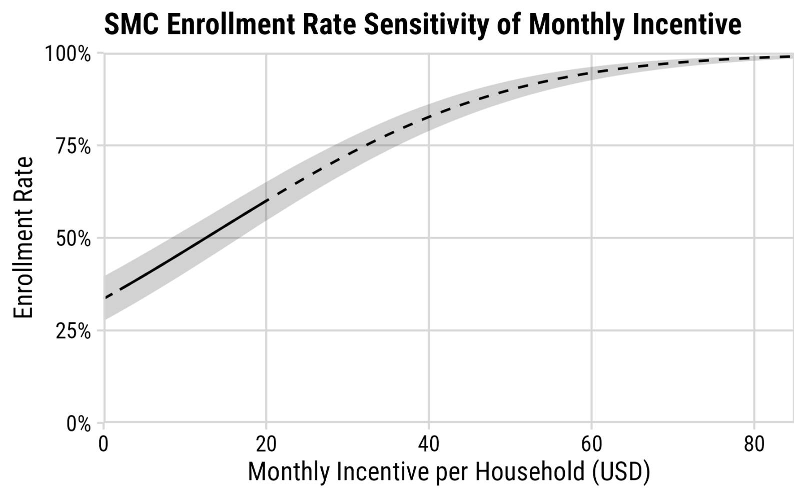


Figure 10: **Predicted SMC enrollment rate as a function of monthly incentive payment per household.** Estimated from a mixed logit model fitted to a discrete choice experiment with 1,356 BEV owners (Hu et al., 2025a). The solid line covers the \$2 – \$20 range directly observed in the survey; the dashed line extrapolates model predictions to higher incentive levels. The shaded band is the 95% confidence interval. At zero incentive, approximately 30.0% of owners enroll voluntarily; a \$20 payment reaches approximately 60.0%; and 100% enrollment requires \$85 per month. The concave shape reflects diminishing marginal returns: each successive dollar of incentive yields smaller enrollment gains at higher participation levels.

This diminishing return is amplified at the program level: increasing the monthly incentive to attract marginal participants also raises costs for all existing enrollees, since utilities must offer a uniform payment. Consequently, total program cost scales non-linearly with enrollment, suggesting an optimal enrollment level where marginal peak-shaving benefits justify marginal incentive costs.

3.1.3 Simulation Process

3.1.3.1 Step 1: BEV charging load profile

The simulation assumes 200-mile range BEVs (48.4 kWh battery, 0.242 kWh/mile efficiency) with 90% efficiency of Level 2 residential charging (7.2 kW times 90%) and 20 – 80% state-of-charge constraints (Tarroja et al., 2016; Xu et al., 2025). At 15-minute resolution (35,040 annual intervals), the model tracks current SOC, energy consumption from travel, charging opportunities, and charging needs. The resulting charging load profile, without any shifting, follows a normal distribution which peaks at 7 PM (19:00). See Figure 11 for the BEV charging load with 10,000 vehicles simulated with realistic travel patterns from NHTS (NHTS, 2022).

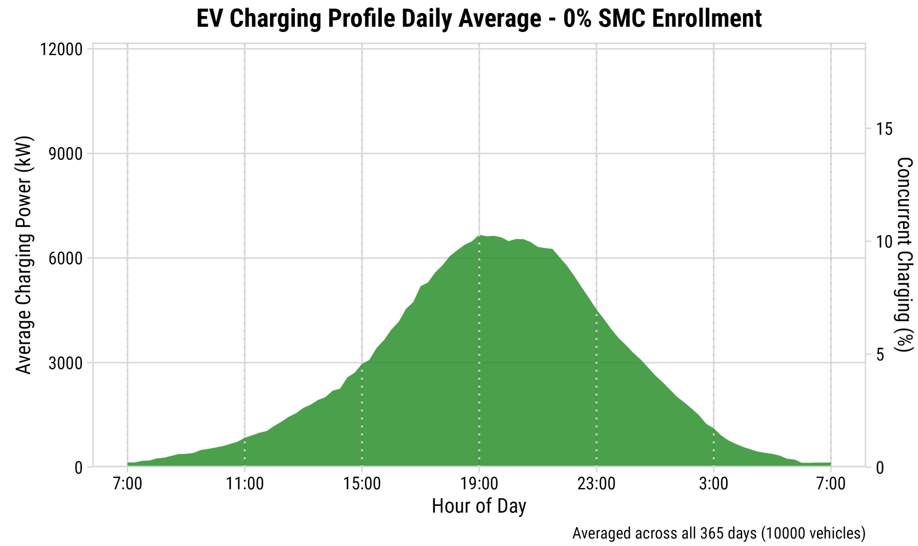


Figure 11: **BEV charging load profile.** Simulation of 10,000 vehicles with realistic travel patterns from NHTS (NHTS, 2022), producing an unmanaged charging load profile that peaks at 7 PM.

3.1.3.2 Step 2: BEV charging load peak shaving

The peak-shaving algorithm reassigns BEV charging from the *normal* window to the *valley* window using two protective conditions. During the *normal* window, which begins at 10 AM, charging is suppressed unless the SOC would fall below 20% or delaying would prevent the vehicle from meeting its next-day travel requirements. During the *valley* window, deferred demand is delivered at maximum rate until the SOC reaches 80% or the valley period ends. Charging sessions that cannot be shifted under these constraints remain in their original time slots and are classified as *override* events (Hu et al., 2025a); across all simulation scenarios, override frequency stays within 2 – 3 events per vehicle per month.

Five transition times from *normal* to *valley* mode are compared (8 PM, 9 PM, 10 PM, 11 PM, and 12 AM). Figure 12 shows the resulting BEV-only peak at 50% SMC enrollment across all five configurations. This BEV-only shifting tends to generate a new peak in the *valley* window, which is not the case if stacked on top of the grid net load.

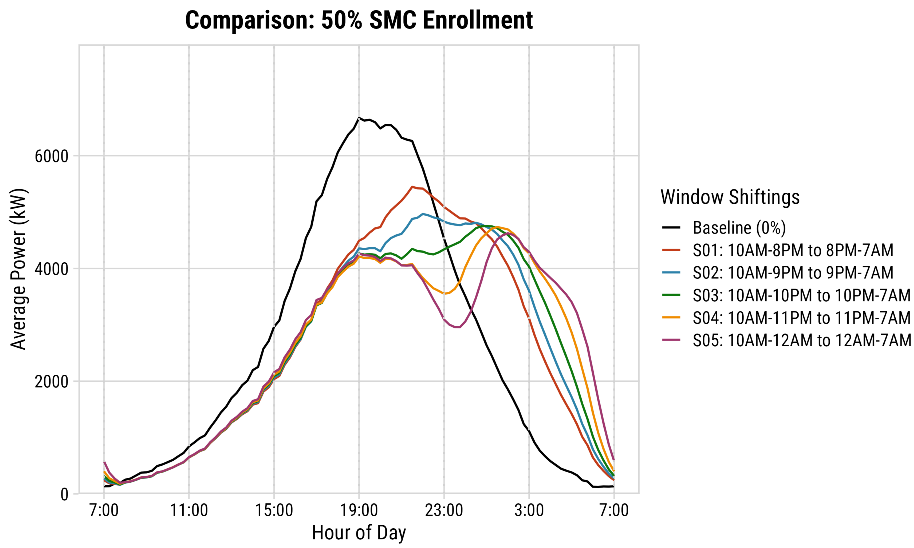


Figure 12: **BEV charging load peak shaving across five valley-transition configurations.** BEV charging peak at 50% SMC enrollment for five transition times from normal to valley mode (8 PM – 12 AM).

3.1.3.3 Step 3: Grid net load profile

The grid baseline is constructed from historical net load time series obtained from GridStatus.io for CAISO and NYISO at 5-minute resolution, aggregated to 15-minute intervals after cleaning. Net load is defined as total electricity consumption minus variable renewable generation, primarily solar and wind, representing the portion of demand that must be served by dispatchable resources. Full-year 2025 data are used as the primary baseline.

Two analytical modes are applied: a full-year average profile formed by averaging all 365 daily traces into a single representative 24-hour curve, and individual single-day or seasonal-average profiles for extreme and seasonal analyses.

Figure 13 shows the 2025 average daily net load for CAISO, which exhibits a characteristic midday dip driven by solar generation and a steep evening ramp. Our focus is the evening peak and the succeeding overnight valley, which together define the window of opportunity for SMC to shift BEV charging load and reduce peak demand. The NYISO net load profile (not shown) has a different shape, with a more gradual ramp and no pronounced midday valley, reflecting its different generation mix and demand patterns.

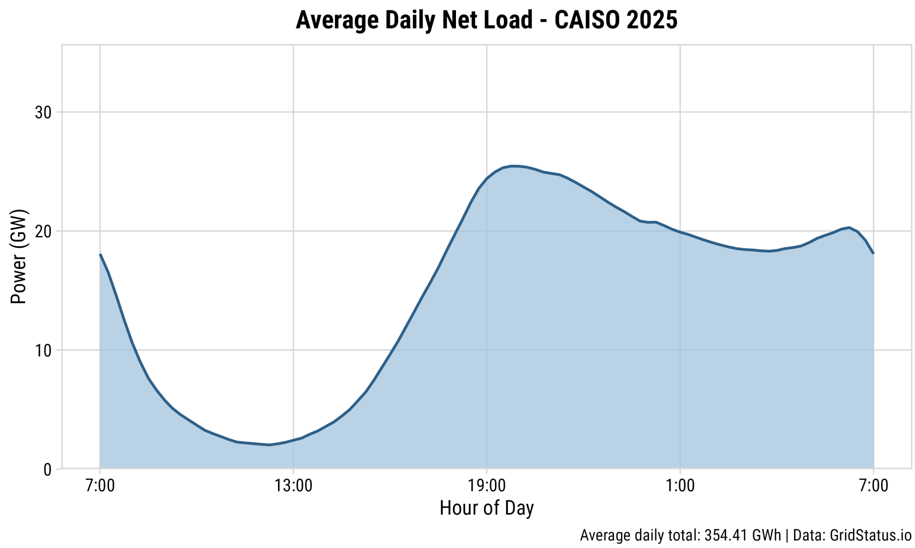


Figure 13: **Grid net load profile.** 2025 average daily net load profile for CAISO from GridStatus.io, representing the grid baseline onto which simulated BEV charging load is stacked. Net load equals total consumption minus variable renewable generation.

3.1.3.4 Step 4: BEV + net load profile and peak shaving

To compute grid-level impacts, the simulated BEV charging load is scaled to match regional fleet sizes and stacked on top of the net load baseline. The simulation sweeps across two sensitivity dimensions:

1. Five TOU load-shifting window configurations, defined by the transition time from *normal* to *valley* mode (8 PM, 9 PM, 10 PM, 11 PM, and 12 AM).
2. SMC enrollment levels from 0% to 100% in 10% steps.

All simulations assume a 1:1 BEV-to-household ratio, representing full BEV adoption among detached single-family households; sensitivity to adoption rates is reported in Appendix B.

Date ranges span extreme single days, seasonal averages, and the full-year mean, providing temporal robustness checks across varied grid conditions.

With this simulation setup, all BEVs can guarantee their travel needs while participating in the SMC program. The travel patterns are not altered by the charging program with or without peak shaving.

For each simulation, we use the 10,000 vehicles modeled with realistic travel patterns from NHTS (in Step 1) (NHTS, 2022), and each simulated vehicle represents

769 (7.69 million / 10,000) vehicles for CAISO, and 316 vehicles for NYISO as scaled results. The vehicles start the year with random SOC between 20% and 80%, and follow their travel patterns throughout the year. When parked at home, they are eligible for Level 2 charging at 6.48 kW (7.2 kW times 90% efficiency).

Figure 14 shows the combined grid load for CAISO under annual average conditions with a 1:1 BEV adoption ratio.

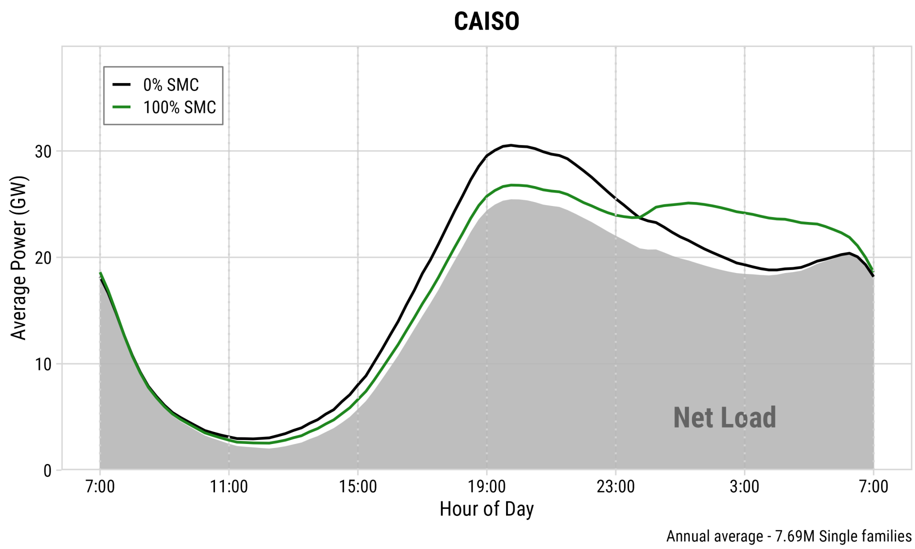


Figure 14: **BEV + net load profile and peak shaving.** Combined BEV and grid net load for CAISO under annual average conditions, 1:1 BEV adoption. The shaded area represents the grid baseline; black and green lines show total load at 0% and 100% SMC enrollment, illustrating how the peak-shaving algorithm reduces the evening peak while redistributing load to the overnight valley.

3.1.3.5 Step 5: Cost efficiency analysis

The peak-shaving results from Step 4 are joined with the consumer enrollment model (Figure 10) to evaluate program cost efficiency. For each enrollment level, the corresponding monthly per-household incentive is read from the enrollment curve; total monthly program cost is then the incentive multiplied by the number of enrolled households. Because the enrollment-to-incentive relationship is concave, program costs scale nonlinearly: each additional percentage point of participation requires a disproportionately larger incentive that must also be paid to every existing enrollee, producing sharply increasing marginal costs at high enrollment levels.

Cost efficiency is expressed as the achieved peak reduction (GW) per unit of monthly program expenditure (million USD). Figure 15 shows the relationship between monthly incentive payment and peak reduction at varying enrollment levels, while Figure 16 presents the resulting efficiency frontiers for CAISO and NYISO, comparing the two regions across all adoption and date-range scenarios evaluated above. The rightmost curve in Figure 16 represents the best cost efficiency and is thus selected for the final cost efficiency plots, such as Figure 20 and Figure 23.

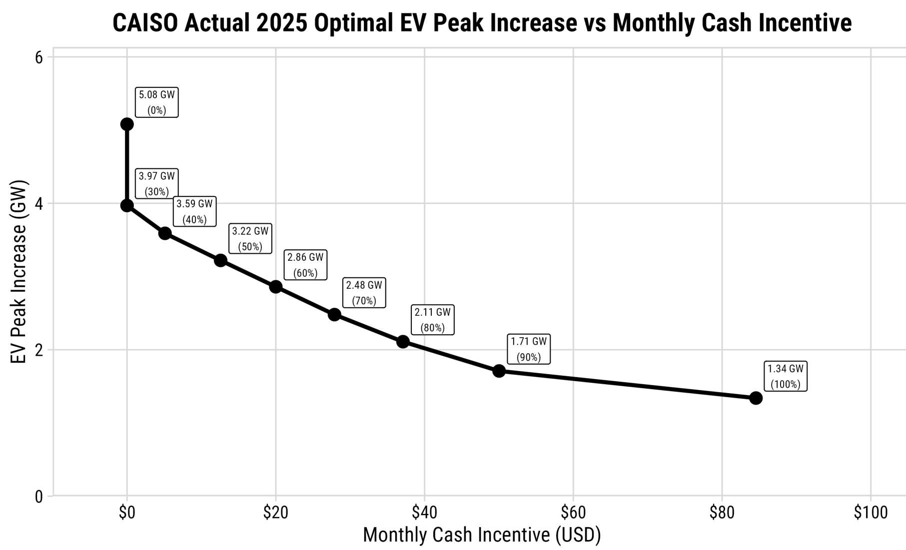


Figure 15: **Incentive payment versus peak reduction.** Monthly incentive payment per household versus achieved peak reduction for CAISO and NYISO under the annual average scenario. Each point represents a 10% SMC enrollment increment.

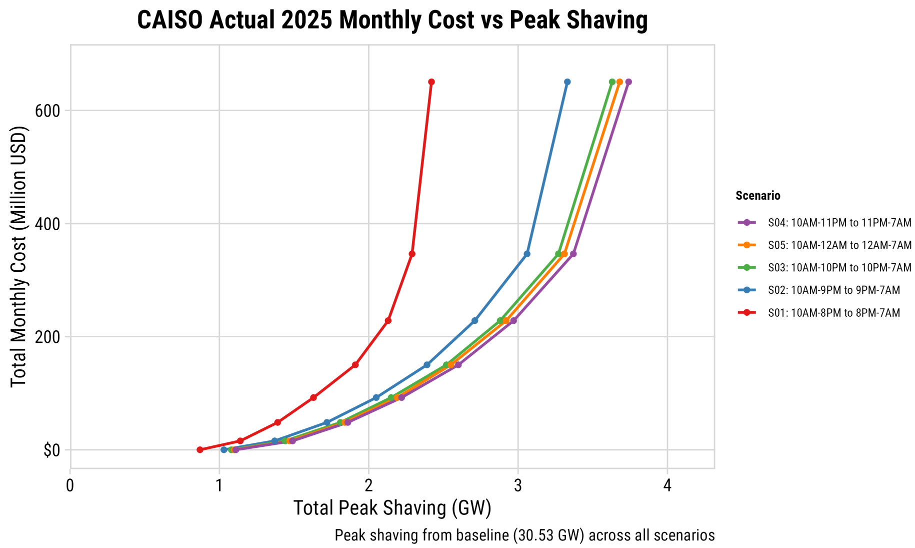


Figure 16: **Cost efficiency frontiers.** Total peak shaving (GW) versus total monthly program cost (million USD) at each 10% enrollment increment and BEV adoption level for CAISO and NYISO. Secondary axes show per-household peak shaving (W) and monthly per-household cost (USD).

3.2 Results

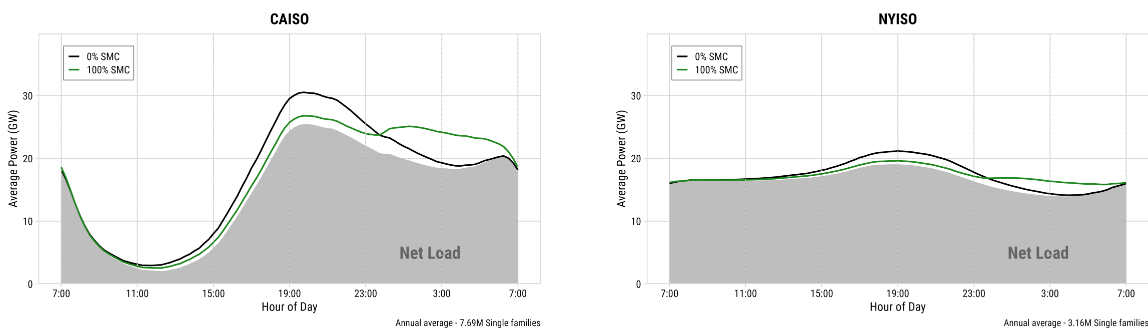
Across all scenarios, SMC participation is the primary lever on peak reduction. We therefore report peak shaving and its associated cost efficiency as functions of enrollment, proceeding through the three temporal conditions in turn and beginning with annual averages.

3.2.1 Annual Average Peak Shaving

The 2025 average daily net load profiles for CAISO and NYISO (Grid Status, 2026a; 2026b) reveal distinct regional patterns (Figure 17). CAISO exhibits a pronounced evening peak around 7 – 9 PM and a nighttime valley around 11 PM – 5 AM. Notably, CAISO's profile also displays a primary daytime valley in net demand driven by high solar generation, reflecting California's substantial solar capacity rather than low total demand. NYISO peaks slightly earlier (6 PM – 8 PM) with a nighttime valley around 11 PM – 7 AM. We target the nighttime valley for managed charging because residential charging predominantly occurs in the evening and nighttime hours when vehicles are parked at home, and nighttime electricity prices are substantially lower.

All load profiles in this study are plotted starting from 7 AM rather than the conventional midnight (12 AM). This choice reflects the natural arc of a typical household day: residents wake around 7 AM, leave for work or daily activities, return home in the evening, plug in their vehicles, and sleep through the early morning hours. Anchoring the x-axis at 7 AM keeps the evening peak, which is the primary focus of peak-shaving analysis, near the center of the chart, and groups the overnight valley period, where SMC delivers its deferred charging, into a contiguous block at the right, making the charge-shifting logic visually intuitive.

When unmanaged BEV charging is stacked on the grid net load, it amplifies the evening peak in both regions. Relative to unmanaged charging, full SMC enrollment in CAISO reduces the net demand peak by 3.7 GW (from 30.5 GW to 26.8 GW), a 12.1% reduction (Figure 17 A). NYISO achieves a smaller reduction of 1.6 GW (from 21.2 GW to 19.6 GW), or 7.5% of the original peak (Figure 17 B).



(a) CAISO 2025 annual average

(b) NYISO 2025 annual average

Figure 17: **2025 average daily grid load and peak shaving of CAISO and NYISO.** Shaded area represents net load; black and green lines show total grid load with 0% and 100% SMC enrollment, respectively. (A) CAISO: evening peak shaved by 3.7 GW (12.1%) under full SMC enrollment; the daytime valley reflects California's substantial solar capacity. (B) NYISO: evening peak shaved by 1.6 GW (7.5%) under full SMC enrollment.

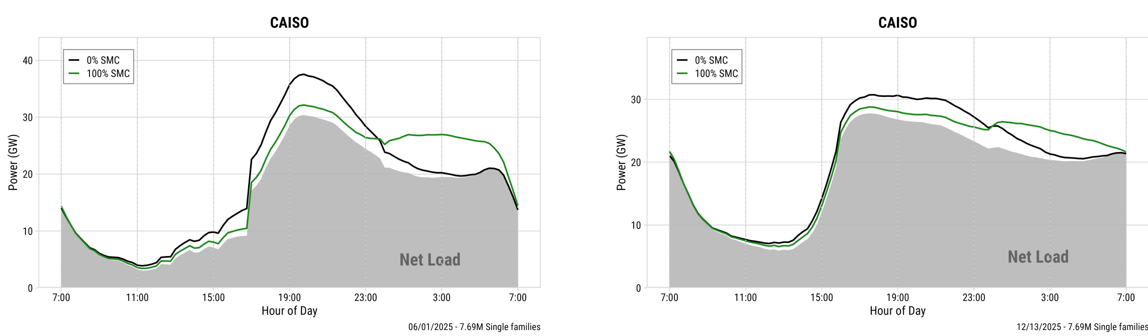
3.2.2 Extreme Peak-Shaving Days

Beyond annual averages, peak-shaving performance varies considerably from day to day. Table 5 summarizes the days with the most and least peak shaving for each region in 2025, showing the original peak, the shaved peak under 100% SMC enrollment, and the resulting peak shaving percentage. Extreme days are ranked by the largest achievable peak reduction under full SMC enrollment, not by the highest absolute grid demand, because the operational value of an SMC program is determined by how much peak it can shave rather than by the level of the peak itself.

Table 5: **Extreme peak shaving days for CAISO and NYISO in 2025.**

Region	Day Type	Date	Original Peak	Shaved Peak	Peak Shaving %
CAISO	Most Peak Shaving	06/01/2025	37.6 GW	32.2 GW	14.4%
CAISO	Least Peak Shaving	12/13/2025	30.7 GW	28.8 GW	6.3%
NYISO	Most Peak Shaving	07/13/2025	27.8 GW	25.6 GW	8.1%
NYISO	Least Peak Shaving	11/08/2025	17.8 GW	17.0 GW	4.9%

CAISO's highest peak-shaving day occurs on June 1st, when SMC reduces the peak by 5.4 GW (from 37.6 GW to 32.2 GW), a 14.4% reduction (Figure 18 A). In contrast, on December 13th, the lowest peak-shaving day, SMC achieves only a 1.9 GW reduction (from 30.7 GW to 28.8 GW), or 6.3% (Figure 18 B). Note that the lowest peak shaving day is based on the constraint in which the load curve is in monotony. The highest and lowest peak-shaving days show the best and worst performance of SMC in CAISO, while the annual average peak-shaving falls in between.



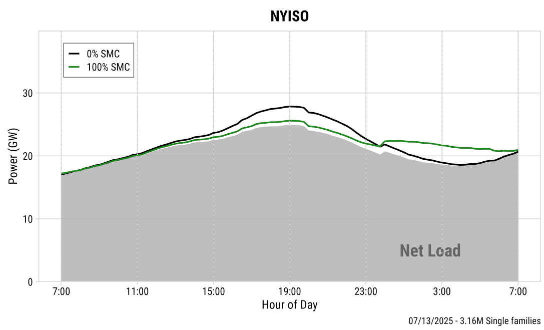
(a) Highest peak-shaving day (June 1st)

(b) Lowest peak-shaving day (December 13th)

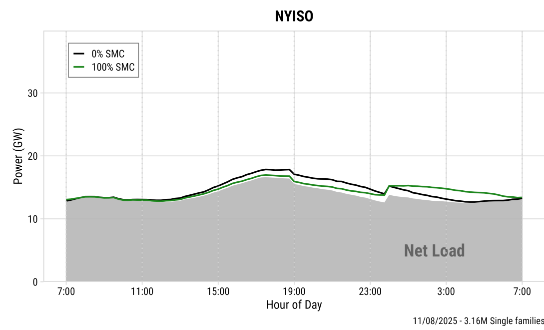
Figure 18: **2025 extreme peak-shaving days of CAISO.** (A) CAISO's highest peak-shaving day occurs on June 1st, with peak reduced from 37.6 GW to 32.2 GW under 100% SMC enrollment. (B) CAISO's lowest peak-shaving day occurs on December 13th, with peak reduced from 30.7 GW to 28.8 GW.

NYISO exhibits a similar pattern but with smaller magnitudes. On July 13th, the highest peak-shaving day, SMC achieves a 2.3 GW reduction (from 27.8 GW to 25.6

GW), or 8.1% (Figure 19 A). On November 8th, the lowest peak-shaving day, SMC achieves a 0.9 GW reduction (from 17.8 GW to 17.0 GW), or 4.9% (Figure 19 B). The smaller absolute reductions in NYISO compared to CAISO reflect the lower number of households (3.16 million vs. 7.69 million) and, consequently, fewer BEVs contributing to the managed charging pool. The smaller percentage reductions in NYISO compared to CAISO reflect the lower daily variability in net load.



(a) Highest peak-shaving day (July 13th)

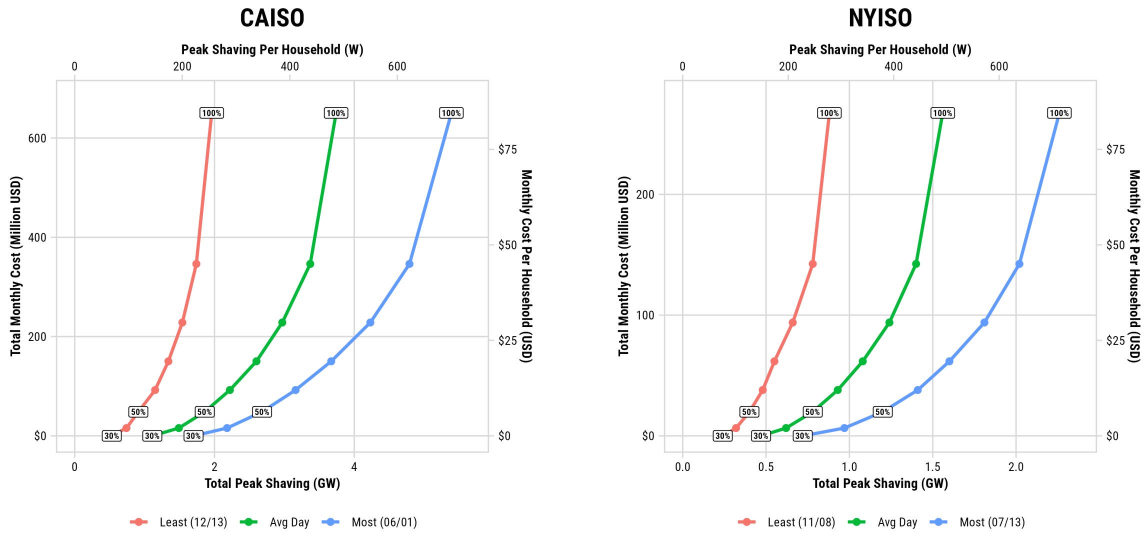


(b) Lowest peak-shaving day (November 8th)

Figure 19: **2025 extreme peak-shaving days of NYISO.** (A) NYISO's highest peak-shaving day occurs on July 13th, with peak reduced from 27.8 GW to 25.6 GW under 100% SMC enrollment. (B) NYISO's lowest peak-shaving day occurs on November 8th, with peak reduced from 17.8 GW to 17.0 GW.

By combining the consumer enrollment model (Figure 10) with the peak-shaving simulation results (Figure 18 and Figure 19), we can evaluate the cost efficiency of SMC programs (Figure 20). Each plot shows three curves representing the highest, average, and lowest peak-shaving cases, with the highest and lowest corresponding to the extreme days discussed above, and the average representing the daily mean across the full year. The primary axes display total peak shaving (GW) versus total monthly cost (million USD) for the entire program, while the secondary axes show per-household peak shaving and per-BEV monthly cost, providing both system-level and individual-level perspectives.

Each dot along the curve represents a 10% increment in SMC enrollment. Because the incentive required to attract each additional participant grows disproportionately with enrollment (Figure 10), the dots become increasingly spaced along the cost axis. This means the cost efficiency of each additional unit of peak shaving diminishes at higher enrollment levels: achieving a desired peak-shaving target is substantially more cost-effective at moderate enrollment rates than at near-full participation.



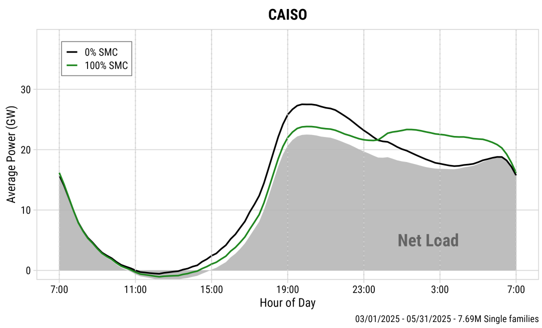
(a) CAISO efficiency frontier (b) NYISO efficiency frontier

Figure 20: **2025 cost efficiency of peak shaving for CAISO and NYISO.** (A) CAISO efficiency frontier showing total peak shaving vs. total monthly cost for highest, average, and lowest peak-shaving days. (B) NYISO efficiency frontier. Each dot represents a 10% enrollment increment. Secondary axes show per-household and per-BEV values.

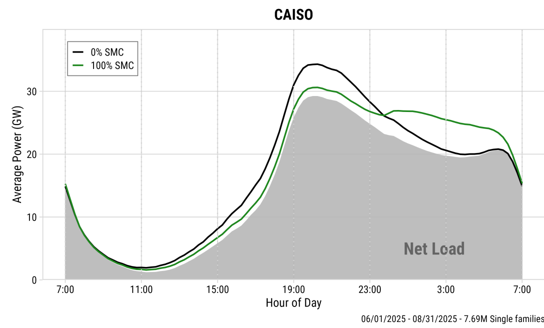
3.2.3 Seasonal Averages

Peak-shaving performance also varies by season. We examine seasonal averages for spring (March to May), summer (June to August), fall (September to November), and winter (December to February).

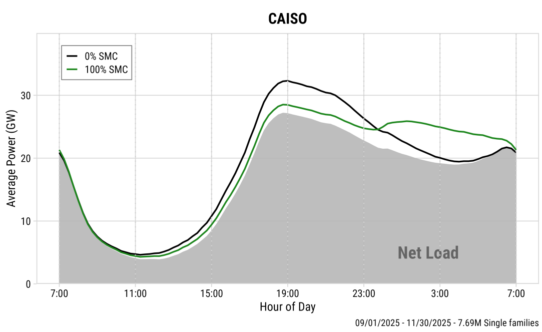
CAISO's seasonal load profiles share a consistent structure across all four seasons (Figure 21). The solar-driven daytime valley is visible year-round as a deep trough near midday, and the evening peak falls consistently around 7 PM (19:00) regardless of season. Absolute peak demand ranges from 27.5 GW in spring to 34.3 GW in summer, driven by air conditioning loads. Despite this range, SMC reduces the evening peak by approximately 3.5 – 4.0 GW at 100% enrollment in every season, a proportional reduction of 10.0 – 14.0%. Morning load levels differ among seasons: beginning at 7 AM, the winter and fall profiles are near 21.0 GW, elevated by overnight space-heating demand, while spring and summer mornings start near 15.0 GW. This variation in morning baseline does not, however, translate into seasonal variation in peak-shaving effectiveness, because the gap between the evening peak and the overnight valley remains wide enough in all seasons to absorb the deferred BEV charging load.



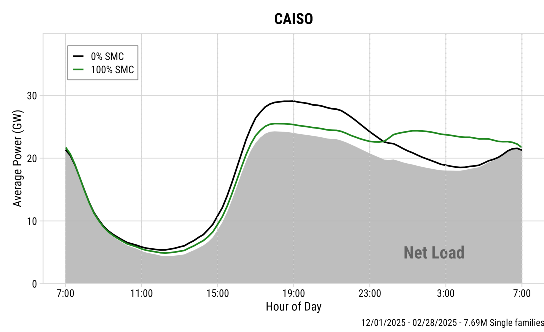
(a) Spring (March – May)



(b) Summer (June – August)



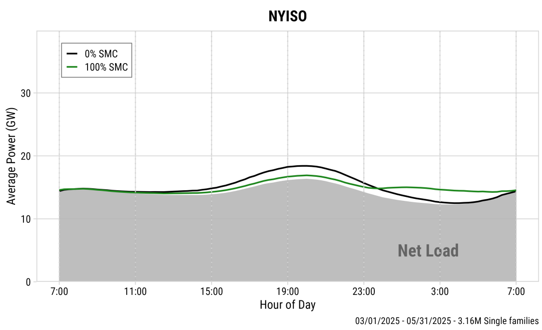
(c) Fall (September – November)



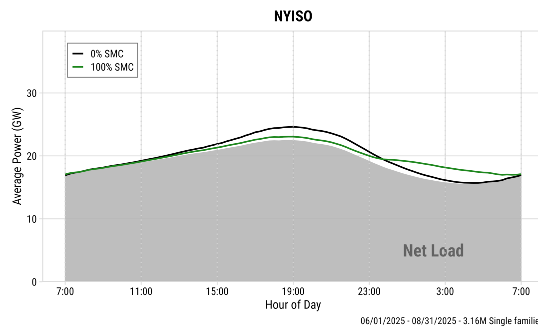
(d) Winter (December – February)

Figure 21: **2025 seasonal average peak shaving of CAISO.** Shaded area represents net load; black and green lines show total grid load with 0% and 100% SMC enrollment, respectively. The solar-driven daytime valley is visible in all panels. (A) Spring (March – May): evening peak 27.5 GW, reduced by 3.7 GW at full enrollment. (B) Summer (June – August): highest seasonal demand 34.3 GW, with 3.7 GW reduction under full enrollment. (C) Fall (September – November): evening peak 32.3 GW, reduced by 3.8 GW. (D) Winter (December – February): elevated morning baseline reflects space-heating demand; evening peak 29.1 GW, reduced by 3.6 GW at full enrollment.

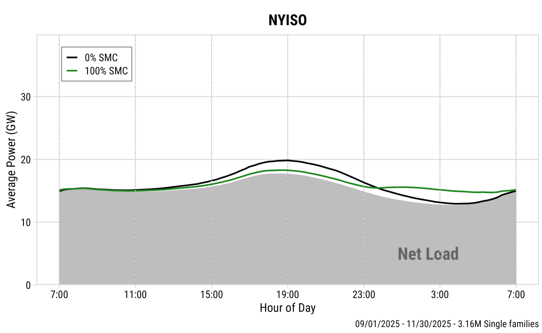
NYISO's seasonal profiles differ fundamentally from CAISO in both shape and available peak shaving opportunity (Figure 22). No solar-driven daytime valley is present in any season; the net load rises gradually through the day to an evening peak near 7 PM (19:00), with the net load occupying a proportionally large share of the profile throughout. Summer demand has the highest peak at 24.7 GW, while spring averages the lowest at 18.4 GW. The winter profile begins near 18.0 GW at 7 AM, reflecting space-heating demand that keeps overnight load elevated and compresses the effective valley window. At 100% enrollment, SMC reduces the evening peak by approximately 1.5 – 2.0 GW in spring, summer, and fall, with winter showing a somewhat smaller achievable reduction as the elevated overnight net load narrows the space available for deferred charging.



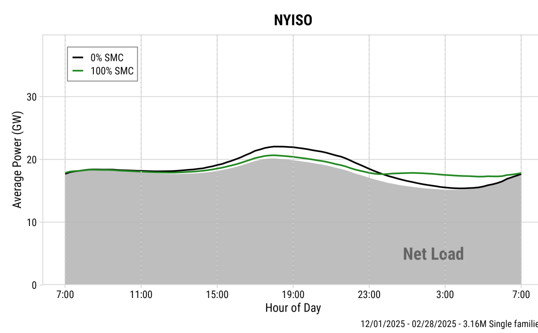
(a) Spring (March – May)



(b) Summer (June – August)



(c) Fall (September – November)

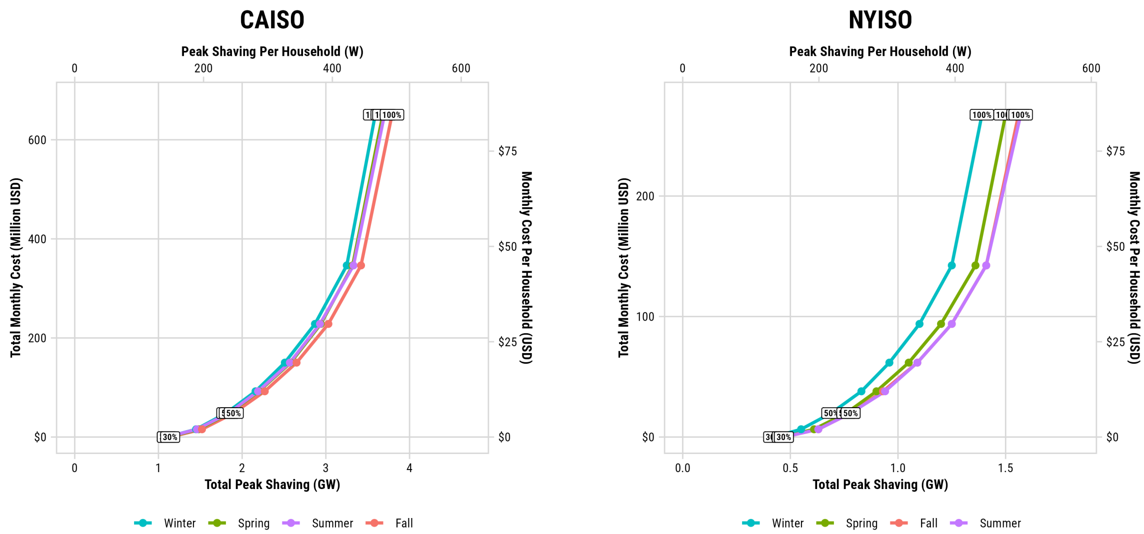


(d) Winter (December – February)

Figure 22: **2025 seasonal average peak shaving of NYISO.** Shaded area represents net load; black and green lines show total grid load with 0% and 100% SMC enrollment, respectively. No solar-driven daytime valley is present in any season, reflecting NYISO's smaller solar generation. (A) Spring (March – May): flattest profile, peak at 18.4 GW, reduced by 1.5 GW at full enrollment. (B) Summer (June – August): highest seasonal demand of 24.6 GW, with 1.6 GW reduction under full enrollment. (C) Fall (September – November): peak at 19.8 GW, reduced by 1.5 GW. (D) Winter (December – February): elevated overnight baseline from space-heating demand narrows the valley window; peak near 22.1 GW with the smallest seasonal shaving of 1.4 GW.

The seasonal efficiency frontiers reveal a key structural difference between the two regions (Figure 23). In CAISO, all four seasonal curves nearly overlap, tracing the same cost-efficiency relationship regardless of season. This convergence follows from the structural consistency of CAISO's solar-driven load shape: because the midday valley and evening peak maintain similar proportions year-round, the volume of BEV load that can be effectively shifted does not change appreciably with season, and a utility operating a year-round SMC program in CAISO can expect consistent cost efficiency across all months.

NYISO's efficiency curves tell a different story. While spring, summer, and fall cluster closely together, the winter curve diverges, achieving less peak shaving per dollar at every enrollment level. At 100% enrollment, winter delivers 1.4 GW of peak shaving compared to 1.5 – 1.6 GW in the other three seasons. The mechanism is the elevated winter net load: space-heating demand raises overnight electricity consumption, shrinking the valley window into which deferred BEV charging can be directed and increasing the risk that concentrated valley-period charging reconstitutes a new demand peak. This seasonal sensitivity suggests that NYISO utilities may need to account for reduced winter effectiveness when setting enrollment targets or calibrating seasonal incentive levels.



(a) CAISO seasonal cost efficiency (b) NYISO seasonal cost efficiency

Figure 23: **2025 seasonal average cost efficiency of SMC programs for CAISO and NYISO.** Each curve traces total peak shaving (GW) against total monthly program cost (million USD) across the four seasons; dots mark 10% enrollment increments. Secondary axes show per-household peak shaving (W) and monthly cost per household (USD). (A) CAISO: all four seasonal curves nearly overlap, indicating season-invariant cost efficiency driven by CAISO's consistent solar-shaped load profile. (B) NYISO: spring, summer, and fall cluster closely, while the winter curve diverges to show lower peak shaving per dollar at every enrollment level, reflecting elevated overnight net load that compresses the effective valley window.

3.3 Discussion and Conclusion

SMC programs can deliver meaningful peak shaving in both CAISO and NYISO, but the magnitude, cost efficiency, and reliability of that reduction differ substantially between regions and across temporal conditions. CAISO consistently achieves larger absolute reductions, reflecting both its larger household base and its deep nighttime valley well-suited to absorbing deferred charging. NYISO shows smaller reductions but more favorable cost efficiency on a per-household basis, with the important exception of winter, when elevated overnight net load compresses the effective valley window and reduces the benefit of shifting charge to off-peak hours.

Across both regions, diminishing returns to enrollment are evident: moderate participation rates (30.0% – 50.0%) capture most of the achievable peak reduction at a fraction of the cost of near-full enrollment, and there is an upper threshold beyond which additional enrollment is counter-productive. The efficiency frontiers presented here treat each GW of peak reduction as equally valuable, but in practice the marginal value of shaving is higher when the original peak is higher, because wholesale electricity prices (locational marginal prices, LMPs), reliability risk, and generation costs are convex functions of load. This means the frontiers understate the relative value of SMC during the highest-demand periods and overstate it during mild conditions. Beyond peak shaving, SMC programs generate co-benefits that are not captured in the efficiency frontiers reported here, meaning the true cost-effectiveness of these programs is likely higher than the results suggest. Here we discuss some of these other related aspects to our results, starting with a comparison to existing SMC programs.

3.3.1 Comparison with Deployed SMC Programs

In CAISO, the Peninsula Clean Energy (PCE) EV Managed Charging pilot recruited 698 drivers from approximately 17,000 targeted BEV owners, an overall enrollment rate of roughly 4%, rising to 10.6% in the highest-incentive treatment group at $40 per month (Peninsula Clean Energy, 2025). The MCE Sync program achieved approximately 10% enrollment of the serviceable BEV market at a $50 sign-up bonus and $10 per month for events, reducing BEV charging during the 4 – 9 PM peak window by nearly 90% (ev.energy, 2024). Both programs operate well below the 30 – 50% enrollment range at which our simulation captures most of the achievable peak reduction, and near-term deployments should be benchmarked against the left-hand portion of the cost curves in Figure 20.

At the system level, the largest active flexible-load program in CAISO, the Demand Side Grid Support (DSGS) program, enrolled approximately 515 MW of capacity as of late 2024, but roughly 85% of this comes from stationary battery storage rather than managed BEV charging (California Energy Commission, 2025). ChargeWise California targets 300 MW of flexible BEV charging from 275,000 enrolled drivers by 2027, a scale that would fall within the range our simulation models for CAISO under moderate BEV adoption (Lewis, 2025). A recent CEC roadmap projects that unidirectional managed BEV charging could contribute roughly 1,000 – 2,000 MW of demand flexibility during 4 – 9 PM peak hours in California by 2035, with bidirectional vehicle-to-home charging adding a further 3,000 – 4,000 MW, placing our modeled CAISO reductions of up to 5.6 GW at full adoption within the range of state-level long-run projections (Weyl, 2026).

In NYISO, the Con Edison SmartCharge New York program provides the closest empirical analog. An independent impact evaluation covering summer 2018 found 731 enrolled vehicles earning up to approximately $400 per year through registration payments, monthly fees, and summer peak-avoidance incentives (Energy and Resource Solutions, 2019). The evaluated peak load reduction on the NYISO peak day was 100 W per vehicle, a realization rate of 14% against the program's design assumption of 700 W per vehicle, compared with the approximately 500 W per vehicle our NYISO simulation predicts at full enrollment on an annual average day. The evaluation attributed this gap to enrolled vehicles already charging very little during the afternoon peak window, with behavioral shifting toward overnight hours having occurred organically before enrollment. This low realization rate is consistent with our simulation's finding that NYISO yields more modest absolute reductions than CAISO, and it underscores that aggregate peak-shaving benefit in NYISO depends critically on the degree to which enrolled vehicles actually overlap with the grid's peak window.

Across both regions, a concern common to incentive-based programs is that utilities pay upfront to enroll drivers who may later leave or charge outside the managed window, wasting incentive expenditure without delivering load shifting. Evidence from a large-scale field experiment suggests this risk is bounded in practice: 85% of BEV drivers remained on a managed charging tariff through a full twelve-month trial, and manual overrides accounted for only 2.3% of total electricity consumption (Metcalfe et al., 2026). Participants who do leave simply revert to the unmanaged baseline, which the grid is already designed to accommodate, so attrition carries a financial cost to the utility but does not create new grid stress.

3.3.2 Co-Benefits of SMC Beyond Peak Shaving

The efficiency frontiers in this study quantify one dimension of program value: peak load reduction. SMC programs also produce co-benefits that, while harder to monetize, can be substantial. By shifting charging away from evening peaks (when fossil fuel peaking generators are on the margin) to overnight valleys (when lower-emission dispatchable sources are predominant), SMC can reduce the marginal emissions associated with BEV charging (Xu et al., 2025). Concentrating load in the overnight valley displaces the higher-emission units typically called last during demand peaks; moreover, a sustained overnight charging load creates a predictable demand signal that can support further investment in 24/7 renewable generation capacity (Chen et al., 2025). Quantifying this emissions benefit requires accurate marginal emissions factor signals, and research has shown that naive application of average or marginal emissions factors can inadvertently increase grid emissions when signals are noisy or when too many vehicles respond to the same signal simultaneously, pointing to emissions-aware coordination as an open research need (Martin et al., 2025).

At the system level, a large enrolled fleet can provide ancillary services such as frequency regulation through fast-response load adjustment, and sustained peak shaving defers the need for new transmission, distribution, and peaking generation capacity. More broadly, an enrolled SMC fleet constitutes a dispatchable capacity resource: the utility can count on a firm, schedulable demand reduction (measured in kW) rather than merely shifting energy (kWh) across hours. This capacity value is highest during system stress events when LMPs spike due to generation scarcity, transmission congestion, or reliability reserve shortfalls. Existing market structures already compensate demand-side resources on a $/kW basis, including NYISO's capacity market and CAISO's Demand Side Grid Support program (California Energy Commission, 2025), providing a ready valuation framework that future work could apply to SMC fleets to produce efficiency frontiers denominated in avoided capacity cost rather than simple peak reduction.

At the consumer level, managed charging within a constrained SOC window (20 – 80%) limits exposure to high charge levels and reduces depth-of-discharge cycling, which can meaningfully extend battery lifetime (Wikner & Thiringer, 2018). These co-benefits are region- and time-specific, and their magnitude depends on the marginal generation mix at the time of charging and the existing grid infrastructure, and quantifying them rigorously requires additional modeling beyond the scope of this study. The efficiency frontiers presented here should therefore be interpreted as a lower bound on the total value of SMC programs.

3.3.3 Scope and Limitations

Two design choices shape how the simulation is constructed and how its outputs should be interpreted: the selection of extreme days and the use of a deterministic rather than stochastic framework.

Extreme days are defined by the largest peak-shaving delta between unmanaged and fully managed charging, not by the highest absolute net load. On summer heatwave days, grid demand peaks are driven predominantly by air conditioning load, so BEV charging constitutes a small share of total demand and SMC has limited leverage even at full enrollment. On days with moderate absolute load but strong alignment between BEV arrival-home timing and the grid's peak window, SMC has proportionally more leverage. February 23 (CAISO) and September 14 (NYISO) exemplify this: neither is the highest-demand day of 2025, yet both yield the largest achievable reductions under full enrollment (5.6 GW and 2.4 GW, respectively). Selecting days by peak-shaving delta therefore targets program performance bounds rather than grid stress bounds, which is the operationally relevant criterion for utility program planning.

The simulation is deterministic rather than probabilistic. The 10,000-vehicle fleet is drawn from the NHTS with sampling weights preserved, so the aggregate charging profile is a weighted population estimate rather than a stochastic draw. At this scale, vehicle-level behavioral variance averages out, and Monte Carlo confidence intervals would be too narrow to carry interpretive value. Structural uncertainty is addressed instead through the scenario sweep across five TOU configurations, three BEV adoption levels, four seasons, and two grid regions. This sweep spans the plausible outcome space more informatively than stochastic bands within any single scenario, and a utility evaluating program design choices can read the scenario comparisons directly to assess sensitivity to key parameters.

The enrollment curve used in this study was based on a discrete choice experiment (Hu et al., 2025a) and therefore could overstate real-world uptake, since the stated-preference experiment could be subject to hypothetical bias (Hensher, 2010). Indeed, field pilots such as PCE and MCE Sync achieved only 4 – 10% enrollment despite monetary incentives, well below the 30 – 50% range at which our simulation captures most of the achievable peak reduction. As a result, the cost estimates in this study may be a lower bound on the true costs needed to achieve higher enrollment levels. Additionally, on approximately 15.0% of CAISO days, enrollment beyond a certain threshold reconstitutes a new overnight peak, so utilities should not treat 100% participation as a preferred target.

The simulation covers residential Level 2 charging in detached single-family homes only, excluding multi-unit housing, workplace, and public charging. While this was assumed because these are the typical conditions required to enroll in an actual SMC program, the total additional load from BEV charging may be higher from these other charging sources. This exclusion is particularly relevant for NYISO, whose service territory includes New York City where multi-family dwellings constitute a large share of the housing stock. BEV adoption patterns and charging infrastructure access in multi-unit housing differ substantially from single-family homes, meaning the NYISO results may understate total BEV charging load while also missing a population segment that faces different barriers to SMC enrollment. Results are calibrated to 2025 net load data and should not be directly extrapolated to future grids where higher solar penetration or widespread storage will alter net demand profiles, including grids where behind-the-meter solar may shift the preferred charging window from overnight to midday.

The study evaluates only direct load control through SMC and does not consider price-based alternatives, such as "happy hour" tariffs that incentivize voluntary shifting to low-demand periods without requiring session-level control. Such approaches may achieve higher participation rates and warrant comparison against the efficiency frontiers reported here.

The simulation applies a fixed energy consumption rate of 0.242 kWh/mile regardless of season. Cold ambient temperatures reduce battery discharge efficiency and activate cabin heating, increasing per-mile energy demand by roughly 24% in cold climates (Yuksel & Michalek, 2015). For CAISO, California's mild winters make this effect small, and the constant-efficiency assumption introduces negligible bias. For NYISO, winter efficiency degradation would increase charging energy demand beyond what is modeled, further compressing the already-constrained overnight valley window identified above. The current model therefore understates the extent to which NYISO winter performance deteriorates relative to other seasons, making the seasonal divergence result a conservative estimate.

3.3.4 Conclusion

This study integrates empirical consumer enrollment data with a scenario-based grid simulation to evaluate the peak-shaving potential and cost efficiency of supplier-managed charging (SMC) programs in two contrasting U.S. grid regions. SMC can deliver meaningful evening peak reductions in both CAISO and NYISO, but the magnitude, cost efficiency, and reliability of those reductions depend strongly on regional grid structure, season, and enrollment level. CAISO achieves larger absolute reductions, up to 5.6 GW on extreme days, owing to its larger household base and its deep solar-driven overnight valley, while NYISO delivers smaller absolute reductions but more favorable per-household cost efficiency, except in winter when elevated overnight space-heating demand compresses the valley window.

Across both regions, returns to enrollment diminish sharply: moderate participation between 30.0% and 50.0% captures most of the achievable peak reduction at a fraction of the cost of near-full enrollment, and pushing enrollment too high can reconstitute a new overnight peak, which occurs on approximately 15.0% of CAISO days. These results indicate that utilities and policymakers should design SMC programs around moderate, cost-effective enrollment targets rather than maximum participation. Because the efficiency frontiers reported here omit co-benefits such as avoided capacity investment, reduced marginal emissions, and extended battery life, they represent a lower bound on the total value of SMC. Future work integrating these co-benefits, price-based program designs, and higher-renewable future grids will further refine the cost-effective operating envelope for managed charging as BEV fleets continue to grow.

All data and code used to process the data and generate the simulation results are publicly available on GitHub at https://github.com/pingfan-hu/2025-grid-peak-shaving-public. This repository contains all original data, processed data, and simulation outputs, together with a README file documenting the original data sources and providing instructions to reproduce all reported analyses.

Chapter 4: surveydown: An Open-Source, Markdown-Based Platform for Programmable and Reproducible Surveys

Note: This chapter is based on a paper published in *PLOS One* (Hu et al., 2025b).

This chapter 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.

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 chapter 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 chapter details the software design (Section 4.1), describes its key advantages and features compared to existing platforms (Section 4.2), and concludes with a discussion of community adoption, future directions, and limitations (Section 4.3).

4.1 Software Design

4.1.1 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 an MIT license. Figure 24 below is an illustration of the core technologies that form the surveydown platform.

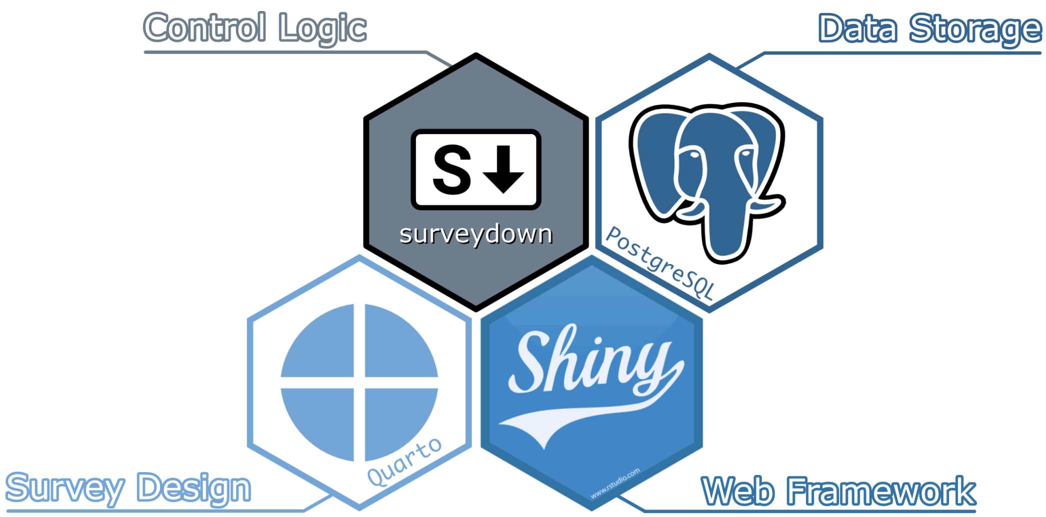


Figure 24: Core technologies in the surveydown survey platform.

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.

4.1.2 Expositional Example

This section presents an expositional example of a two-page survey to explain the basic structure of 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()
```

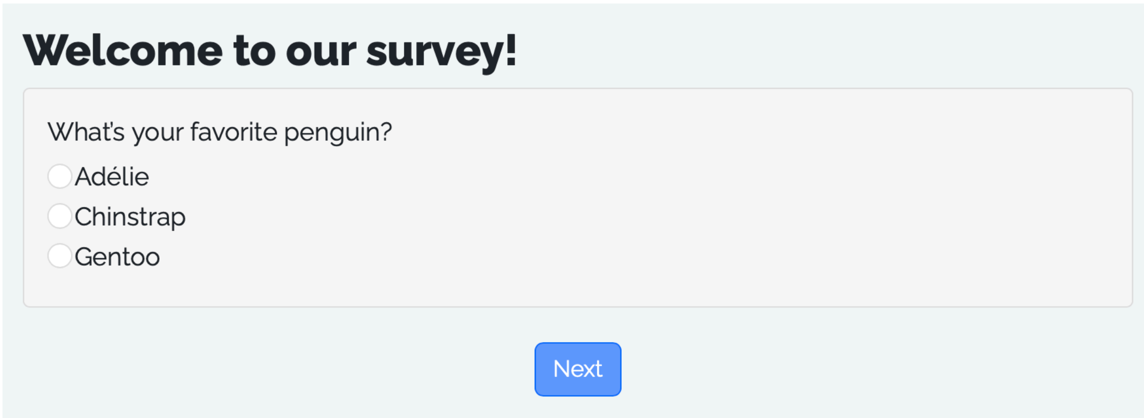
:::
````

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.

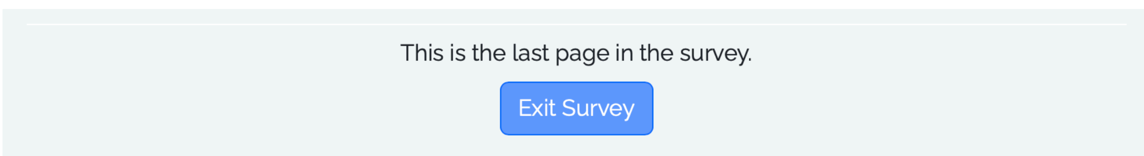
Questions are defined using the `sd_question()` function. In the above example, the `type = "mc"` argument is used to define a multiple choice question. The package supports a wide variety of question types, discussed in detail later in the paper. The `id` argument is set to `"penguins"`, which is the 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 25 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 25: 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:

```r
library(surveydown)

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

# Connect to Database
db <- sd_db_connect()
```

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

# Define the server
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 4.2.3.

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, use the `deployApp()` function from the `rsconnect` package:

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

Figure 26 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 needs 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.

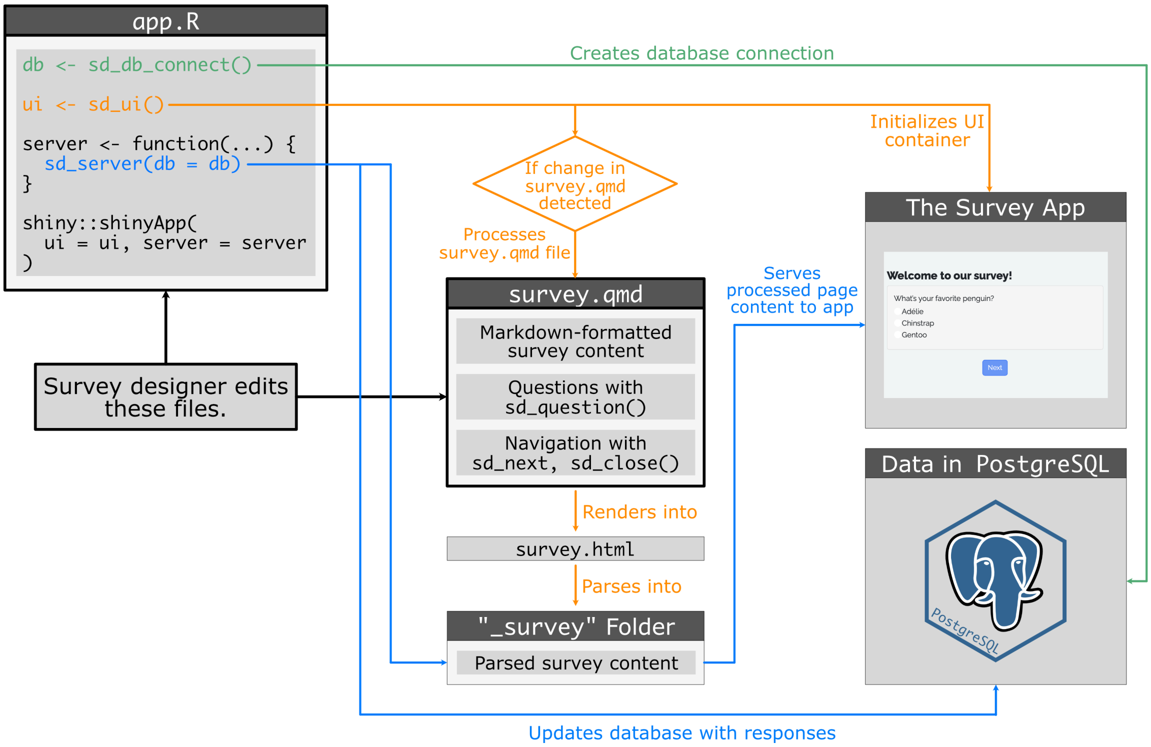


Figure 26: Logic flow diagram of the surveydown survey platform.

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.

4.2 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 reproducible 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.

4.2.1 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 function, 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.

4.2.2 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 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.

4.2.3 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 27 below shows a screenshot of an example survey where users are asked to select the state they live in from the map.

Figure 27: Screenshot of a custom question using the `leaflet` package to display an interactive map.

4.2.4 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 6 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 the 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 & 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 multifactor authentication (MFA) and being SOC 2 and HIPAA compliant.

Table 6: 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

4.3 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 help 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.

Chapter 5: Conclusion and Policy Implications

Chapter 1 outlined the prior research landscape on BEV smart charging adoption, grid peak-shaving, and survey methodology, and identified the knowledge gaps that this dissertation set out to address. The three studies that follow translate consumer preferences into grid-scale program design guidance, evaluate regional cost efficiency under realistic enrollment behavior, and contribute the open-source methodological infrastructure that supported the empirical work.

In Chapter 2, we addressed the gap between technical analyses of smart charging programs and the consumer behavior that determines whether such programs can be deployed at meaningful scale. Through a discrete choice experiment with 1,356 current BEV owners across the United States, we measured how the structure of supplier-managed charging (SMC) and vehicle-to-grid (V2G) programs shapes participation (Hu et al., 2025a). The results reveal distinct preference patterns across the two program types: SMC participants value operational flexibility (guaranteed end-of-charge thresholds and override allowances) together with modest recurring payments, while V2G participants are more sensitive to monetary incentives, reflecting the more active role of bidirectional power flow. One-time enrollment cash, recurring monthly payments, and operational flexibility each contribute differently to enrollment, and programs that offer adequate flexibility can reach at least 50% enrollment without any monetary payment. To make these findings actionable, we built an interactive web application (https://gwuvehicle.shinyapps.io/enrollment_simulator/) that lets utilities and policymakers explore the enrollment implications of any program configuration rather than committing to a single recommended design.

In Chapter 3, we built on the consumer enrollment model from Study 1 to evaluate the peak-shaving potential and cost efficiency of SMC programs at grid scale in two contrasting U.S. regions: the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO). The scenario-based simulation swept across time-of-use load-shifting windows, BEV adoption levels, and the full 0% to 100% range of SMC participation, producing thousands of net-load profiles with and without managed charging. CAISO achieves larger absolute reductions, with up to 5.6 GW on the most favorable day and 3.7 GW (12.1%) on an annual-average day, while NYISO shows smaller absolute reductions but more favorable per-household cost efficiency. The cost-efficiency frontier in both regions is sharply concave: moderate enrollment in the 30% to 50% range captures most of the achievable peak reduction at a fraction of the cost of near-full enrollment, and on approximately 15.0% of CAISO days, enrollment beyond a certain threshold reconstitutes a new overnight peak from concentrated valley-period charging. Cost efficiency is season-invariant in CAISO but deteriorates in NYISO winters, when elevated overnight space-heating load compresses the off-peak valley window. The implication for utility program design is concrete: target moderate enrollment, configure the load-shifting window to match the regional valley, and benchmark deployed programs against the left-hand portion of the efficiency frontier rather than against ideal full-enrollment scenarios.

In Chapter 4, we introduced surveydown, an open-source, markdown-based survey platform built in the R programming language that supports programmable and reproducible surveys (Hu et al., 2025b). Existing survey platforms typically rely on graphical interfaces or spreadsheets to define survey content, making version control, collaboration, and reproducibility difficult; commercial options often require expensive licenses; and few platforms integrate seamlessly with modern data-analysis workflows. surveydown addresses these limitations through three design choices: a plain-text, markdown-based survey definition built on the Quarto publication system; real-time code execution during survey administration via the R Shiny web framework; and a disaggregated architecture in which researchers retain complete control over the survey application, the deployment environment, and the response data store. The platform is available on CRAN under an MIT license, and a companion GUI tool, sdstudio, is in active development to lower the entry barrier for users with limited coding experience while preserving full reproducibility. Beyond its role in this dissertation as the empirical instrument for Study 1, surveydown contributes a methodological foundation that other researchers can adopt to conduct rigorous, programmable, and fully reproducible surveys across diverse research domains.

5.1 Integrated Implications for Utility Program Design

Read together, Studies 1 and 2 produce a coherent operating guideline for SMC program design that no single study could support on its own. Study 1 establishes that meaningful BEV-owner enrollment is achievable through a combination of operational flexibility and modest recurring payments, and that the cost of reaching very high enrollment levels grows disproportionately because each additional percentage point of participation requires a larger incentive that must be paid to every existing enrollee. Study 2 shows that, on the grid side, the marginal value of additional enrollment also diminishes sharply after the 30% to 50% range, and that in some regions pushing enrollment higher is actively counter-productive because concentrated overnight charging reconstitutes a new peak. The two studies therefore converge on the same prescription: utilities should design SMC programs around moderate enrollment targets rather than near-full participation, pair monetary incentives with strong operational flexibility guarantees, and configure the load-shifting window to match each region's valley shape rather than apply a uniform schedule across territories.

For policymakers and regulators, several levers can align consumer incentives with grid benefits. Incentive structures should favor recurring payments and operational flexibility guarantees over large one-time enrollment bonuses, since the former produce more sustained participation and the latter risk paying for enrollees who later drop out. Time-of-use load-shifting windows should be set in coordination with regional net-load profiles, recognizing that CAISO's solar-driven duck curve and NYISO's flatter, heating-driven winter profile call for different optimal windows. State regulators can support these designs through performance-based regulation that ties utility compensation to program outcomes such as enrollment rates, kW of peak reduction delivered, or avoided infrastructure costs, rather than to total incentive spending. Together, these levers can help move SMC programs from the 4% to 10% enrollment achieved in early pilots toward the 30% to 50% range where cost efficiency is highest.

5.2 Methodological Contributions Beyond the Energy Domain

While surveydown was created to support the empirical work of this dissertation, its contribution extends well beyond transportation electrification research. Survey research is foundational to many disciplines, including social science, public health, behavioral economics, education, and public policy, and the methodological constraints that motivated surveydown apply broadly across these fields. Researchers in these domains routinely encounter the same friction we encountered: graphical-interface platforms that resist version control, commercial platforms that lock data behind subscription fees, and survey instruments that cannot be reliably reproduced because their logic lives in proprietary application state rather than in inspectable code. surveydown's combination of plain-text survey definition, programmable interactivity, and disaggregated data storage offers a methodological alternative that any research group with basic R familiarity can adopt, and its open-source license keeps the tool accessible regardless of institutional budget.

More broadly, this work fits within a growing recognition that open-source research infrastructure deserves the same scholarly and policy investment as proprietary alternatives. Recent congressional momentum (U.S. Congress, 2023; 2024) reflects rising acknowledgment that open tools support reproducibility, scientific rigor, and economic accessibility. surveydown's adoption trajectory, with a published methods paper, distribution through CRAN, an active community of early adopters, and a companion GUI tool in development, illustrates the path by which a single research group's tool can mature into shared scientific infrastructure. Continued investment in community-maintained, open-source research tools is essential if the broader research community is to keep pace with the growing complexity of survey-based empirical research.

5.3 Limitations and Future Directions

This dissertation has several limitations worth flagging for future work. Study 1 captures the preferences of current BEV owners, a population that skews wealthier, more male, and more environmentally engaged than the general car-owning public, so the enrollment curves may not generalize cleanly as BEV adoption broadens to more diverse demographic groups. Study 1 also relies on stated-preference data, which is known to overstate willingness to act compared to revealed-preference data from real-world programs; the wide gap between our predicted enrollment and the 4% to 10% rates observed in early field pilots underscores the practical importance of this caveat. Study 2 covers only residential Level 2 charging in detached single-family homes and uses 2025 grid data, which understates total BEV charging load from multi-family, workplace, and public charging contexts and does not extrapolate cleanly to future high-renewable grids. Study 3's surveydown platform, while functional and production-ready, currently requires basic R knowledge to use, and the planned sdstudio GUI companion is still in active development.

Several research directions follow directly from these limitations. Validating the Study 1 choice models against revealed-preference data from deployed SMC programs would resolve the gap between stated and actual enrollment and refine the enrollment curves used in cost-efficiency analyses. Extending the Study 2 simulation framework to additional ISO regions, to higher-renewable future grid scenarios, and to multi-family and workplace charging contexts would test the regional and structural generality of the moderate-enrollment finding. Integrating bidirectional V2G operation into the cost-efficiency framework would let utilities compare capacity-resource value across unidirectional and bidirectional smart charging architectures. For surveydown, the immediate priorities are completing the sdstudio GUI to lower the entry barrier, expanding the library of validated survey templates for common experimental designs, and developing mobile-optimized question types as mobile completion continues to grow across survey research.

Taken together, the three studies of this dissertation contribute both to the practical work of accelerating sustainable transportation transitions and to the methodological foundations on which future empirical research will rest. Study 1 grounds smart charging program design in measured consumer preferences; Study 2 translates those preferences into regional grid-scale guidance on cost-effective program operation; and Study 3 provides the open-source infrastructure that makes rigorous, reproducible survey-based research broadly accessible. The path from BEV charging coordination to a decarbonized transportation system depends on continued progress on all three fronts: technical design that reflects how consumers actually behave, regional implementation that respects local grid context, and methodological tools that let the research community keep producing the evidence on which sound policy can be built.

Appendix A: Supplemental Information for Chapter 2 (Study 1)

A.1 Demographics Summary

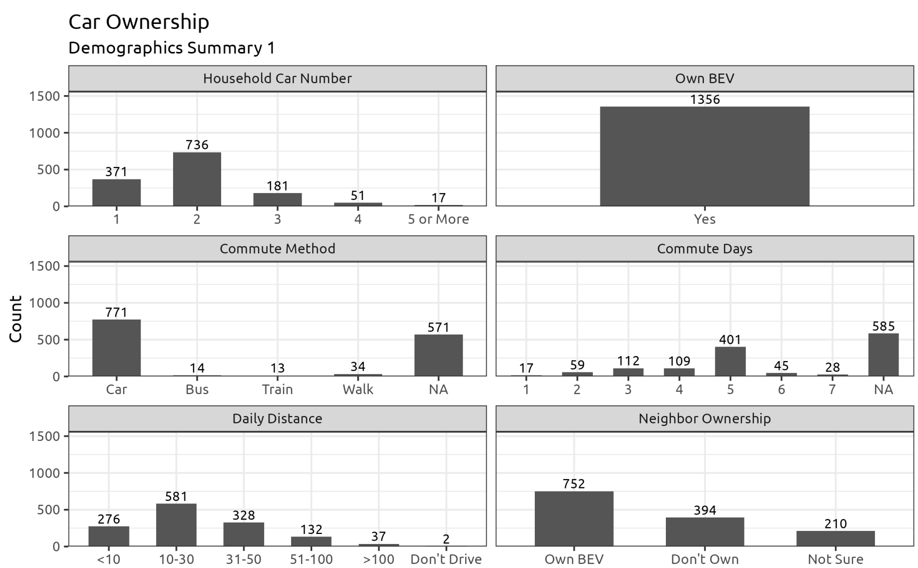


Figure S1: Car Ownership

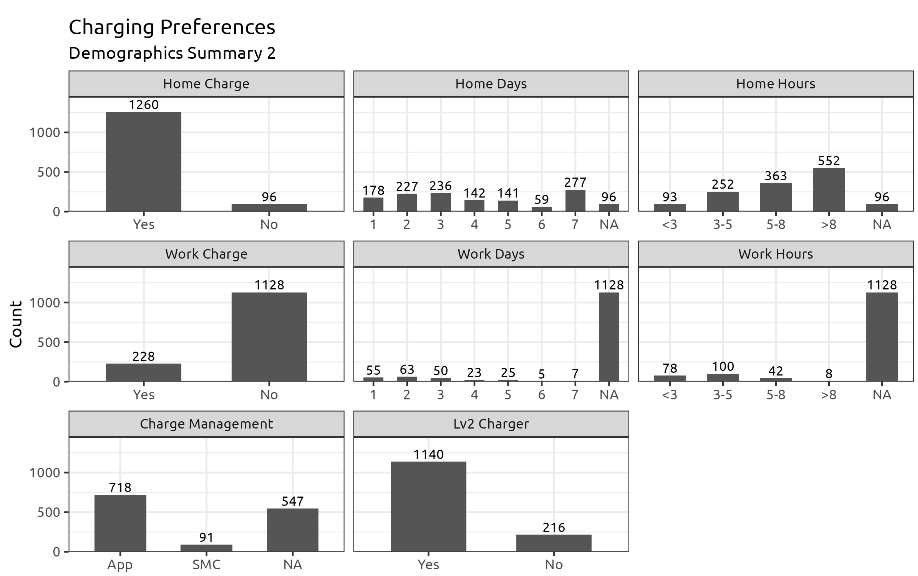


Figure S2: Charging Preferences

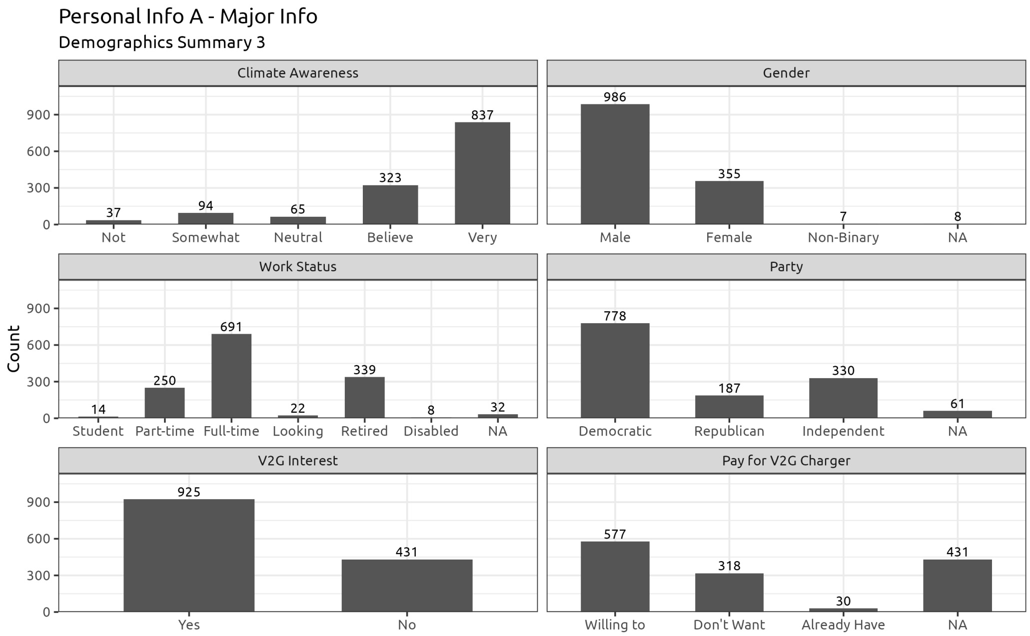


Figure S3: Personal Info A - Major Info

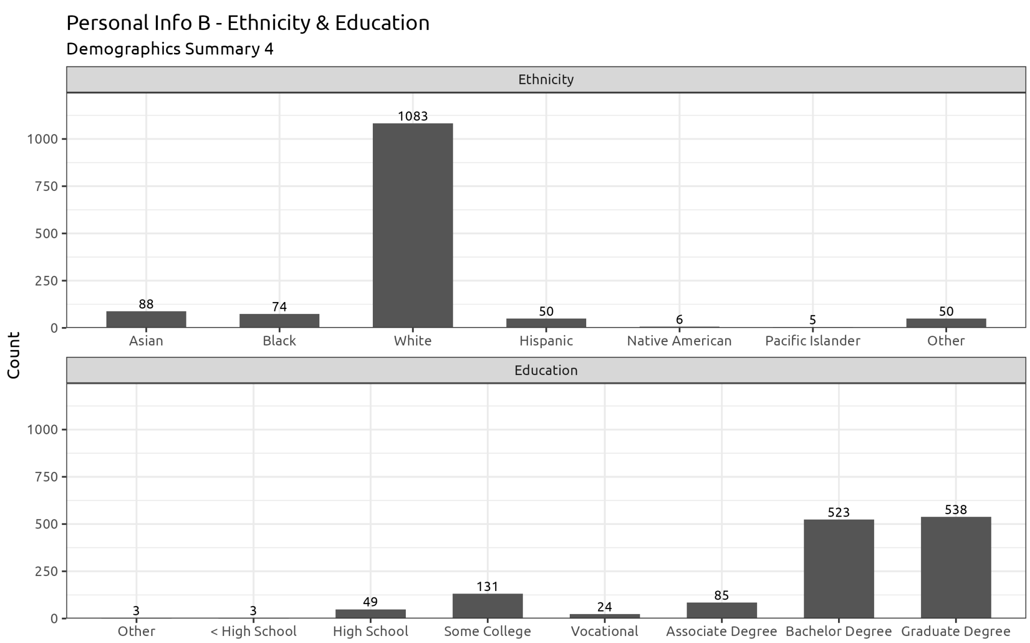


Figure S4: Personal Info B - Ethnicity & Education

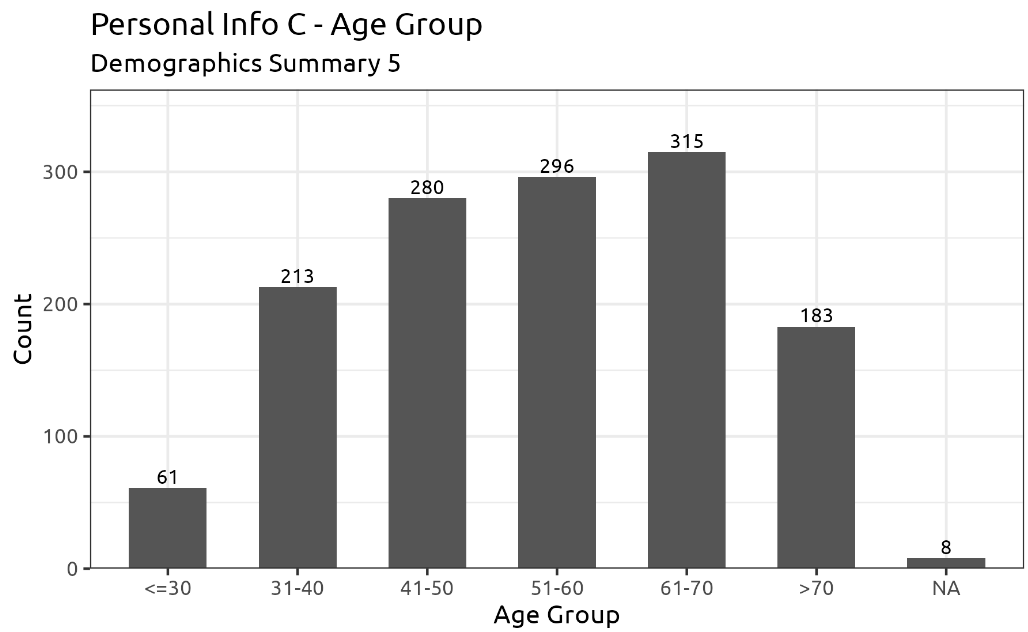


Figure S5: Personal Info C - Age Group

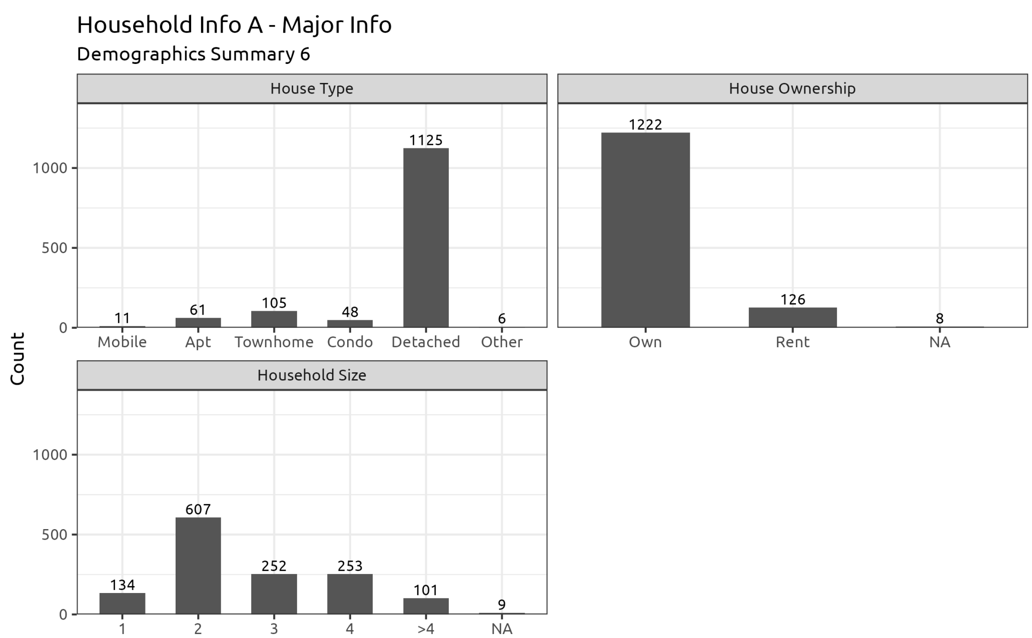


Figure S6: Household Info A - Major Info

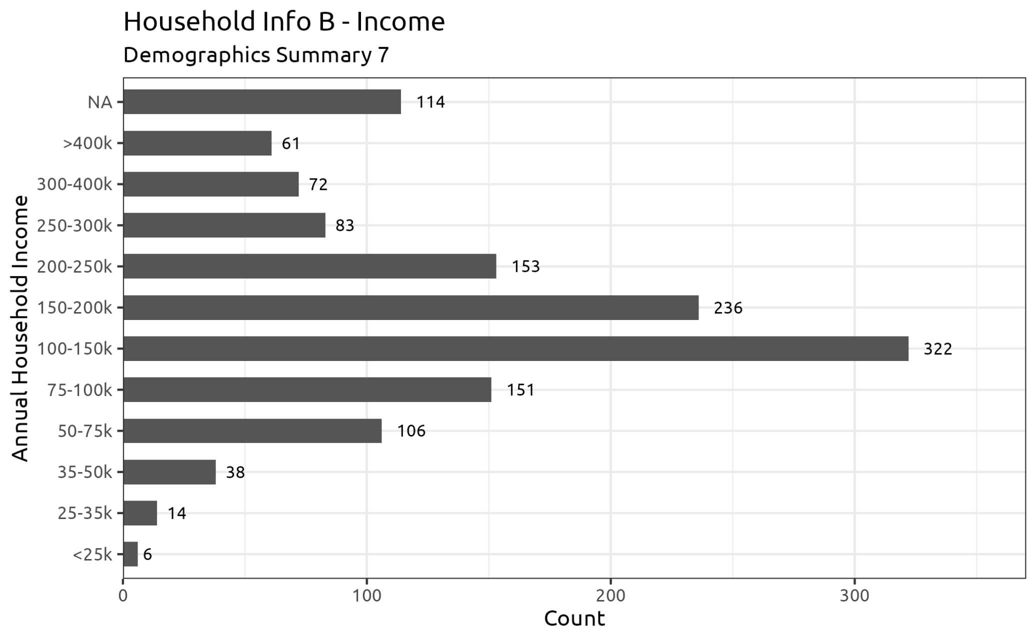


Figure S7: Household Info B - Income

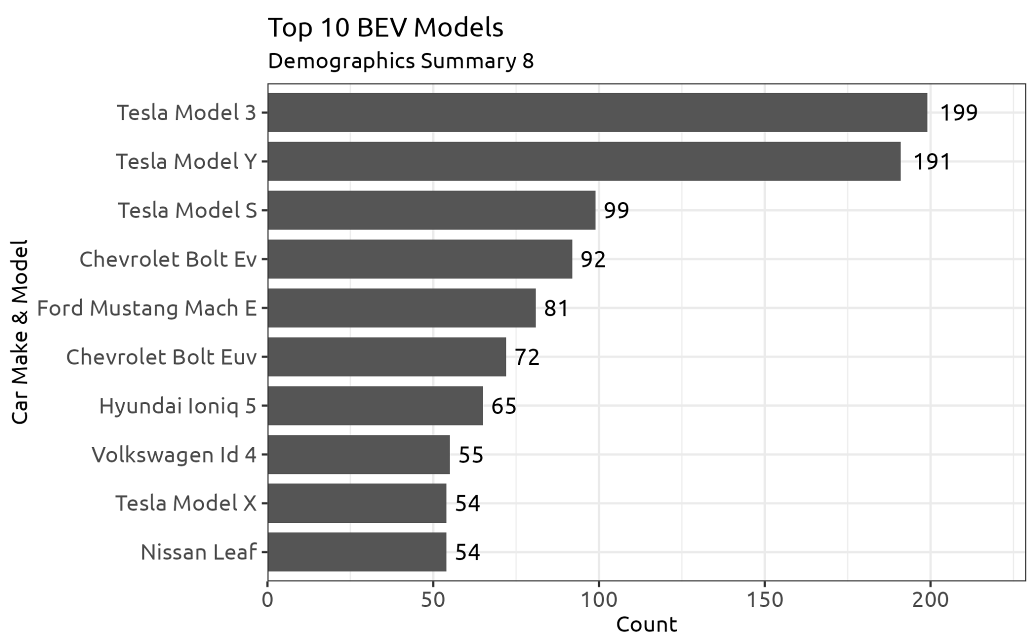


Figure S8: Top 10 BEV Models

Table S1: 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%

N = 1356.

Table S2: 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%

N = 1356.

A.2 Multinomial Logit Models

Table S3: 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.

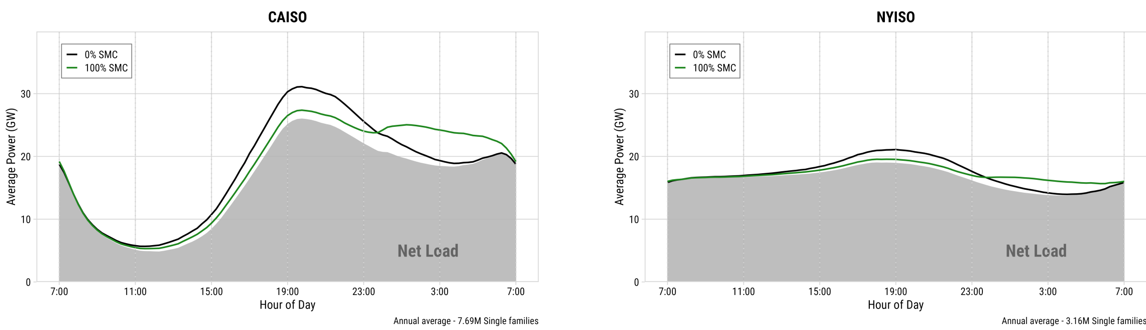
Table S4: V2G Model Coefficients.

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 Table 3.

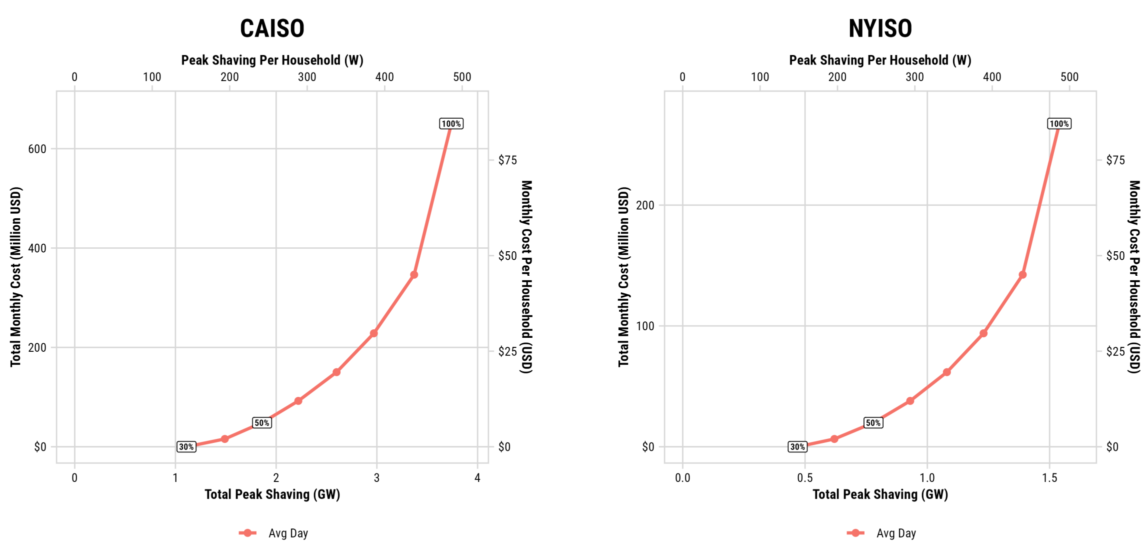
Appendix B: Supplemental Information for Chapter 3 (Study 2)

B.1 2024 Actual Grid Results



(a) CAISO 2024 average (b) NYISO 2024 average

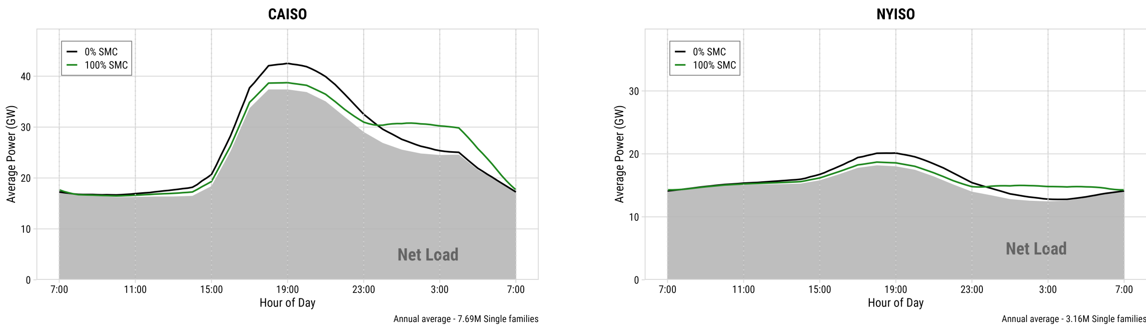
Figure S9: **2024 average daily grid load and peak shaving.** (A) CAISO and (B) NYISO annual-average net load profiles with BEV charging stacked, comparing unmanaged and 100% SMC enrollment scenarios.



(a) CAISO 2024 efficiency (b) NYISO 2024 efficiency

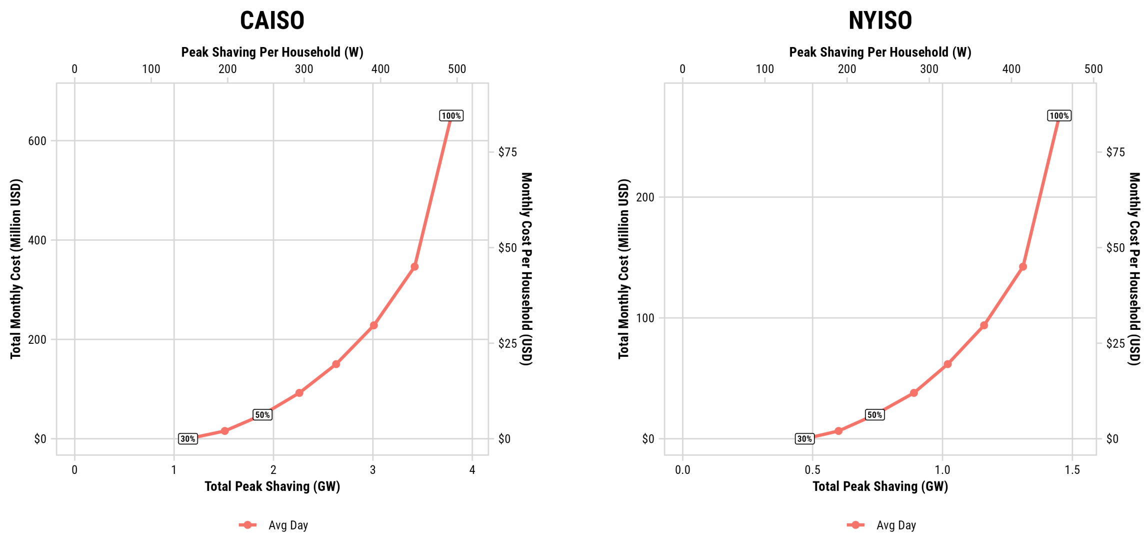
Figure S10: **2024 cost efficiency of SMC programs (annual average).** Total peak shaving versus total monthly program cost for (A) CAISO and (B) NYISO across all BEV adoption levels.

B.2 NLR Cambium Projected Grid Results



(a) CAISO Cambium projection (b) NYISO Cambium projection

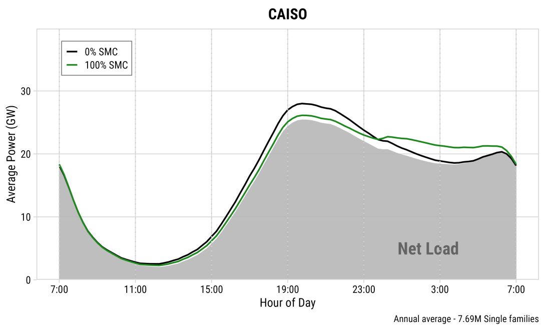
Figure S11: **Cambium 2025 projected average daily grid load and peak shaving.** (A) CAISO and (B) NYISO projected net load profiles with BEV charging stacked under the NLR Cambium 2025 Mid-case scenario.



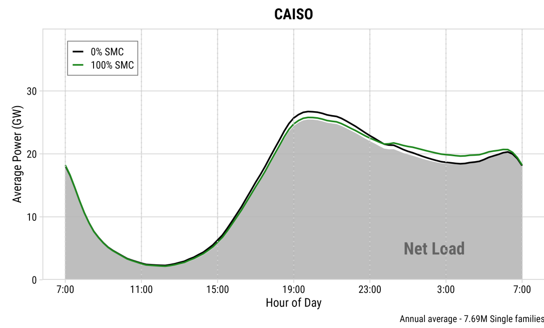
(a) CAISO Cambium efficiency (b) NYISO Cambium efficiency

Figure S12: **Cambium 2025 cost efficiency of SMC programs (annual average).** Total peak shaving versus total monthly program cost under NLR Cambium 2025 projections for (A) CAISO and (B) NYISO across all BEV adoption levels.

B.3 BEV Adoption Rate Sensitivity

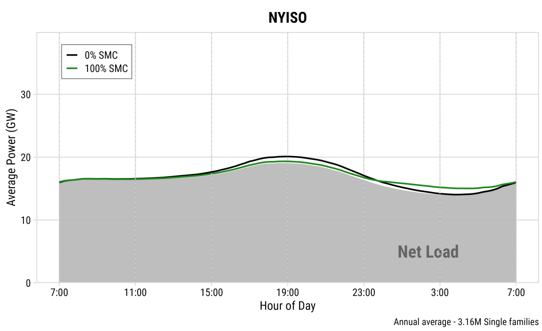


(a) 1:2 BEV-to-house ratio

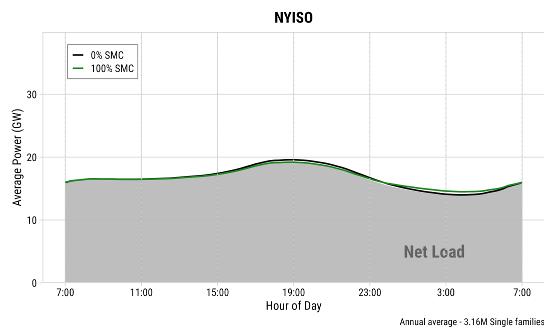


(b) 1:4 BEV-to-house ratio

Figure S13: **Annual average peak shaving across BEV adoption rates for CAISO.** CAISO annual-average net load profiles with BEV charging at (A) 1:2 and (B) 1:4 BEV-to-house adoption ratios.

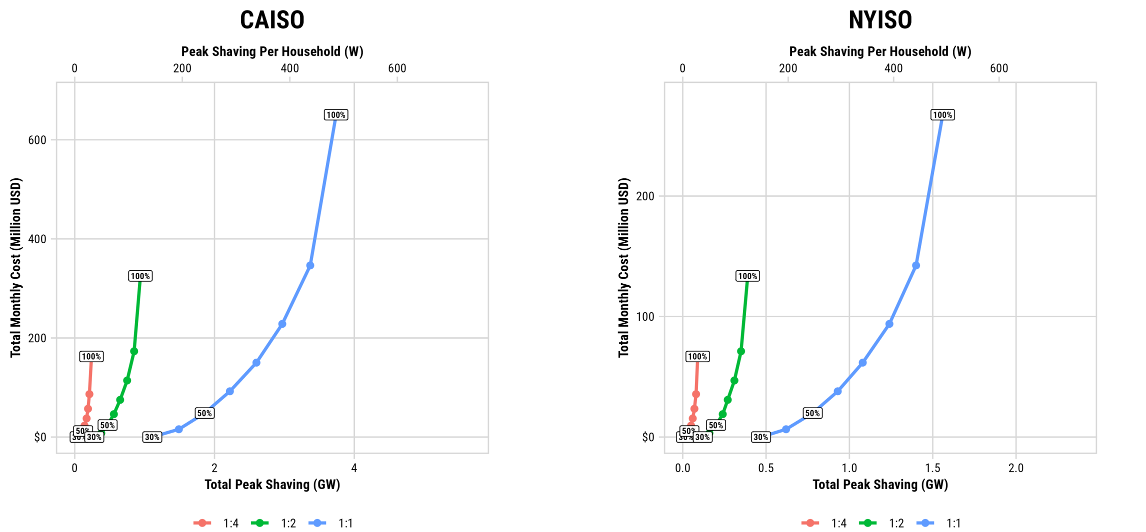


(a) 1:2 BEV-to-house ratio



(b) 1:4 BEV-to-house ratio

Figure S14: **Annual average peak shaving across BEV adoption rates for NYISO.** NYISO annual-average net load profiles with BEV charging at (A) 1:2 and (B) 1:4 BEV-to-house adoption ratios.



(a) CAISO efficiency across adoption ratios

(b) NYISO efficiency across adoption ratios

Figure S15: **Cost efficiency across BEV adoption rates.** Total peak shaving versus total monthly program cost at all three BEV adoption levels for (A) CAISO and (B) NYISO.

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