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Peer-to-Peer Residential Charger Sharing: Exploring Public Perceptions in California

THESIS

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MASTER OF SCIENCE

in

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by

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DEDICATION

To

my family and friends

for their unwavering support and love,
and for inspiring me to dream beyond limits.

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This thesis is based on a manuscript of which I am the first author, and my advisor is a co-author.

ABSTRACT OF THE THESIS

Peer-to-Peer Residential Charger Sharing: Exploring Public Perceptions in California

by

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Master of Science in Civil and Environmental Engineering

University of California, Irvine, 2024

Professor Matthew D. Dean

The widespread adoption of electric vehicles (EVs) faces significant infrastructure challenges, particularly regarding charging accessibility. This thesis investigates peer-to-peer residential charger sharing (P2P-EVSE), an innovative system that connects households with underutilized electric vehicle supply equipment (EVSE) to EV drivers seeking convenient charging options. This research examined the feasibility and acceptance factors of P2P-EVSE platforms through a comprehensive survey of 367 California households with EVs. The study employed a mixed-methods approach, combining quantitative survey analysis with qualitative assessment of user preferences and concerns. The survey instrument included questions about charging habits, sharing preferences, economic motivations, personality traits, and demographic characteristics.

Analysis of survey responses revealed that 28% of respondents showed interest in hosting their chargers, while 31% expressed willingness to rent through P2P-EVSE platforms. Statistical analysis identified economic incentives, outgoing personality traits, and support for alternative charging policies as the strongest predictors of participation intention. Hosts prioritized damage reimbursement guarantees and equipment control,

while renters emphasized convenience and cost savings. Both groups cited liability concerns as the primary participation barrier, with environmental benefits being a secondary consideration. The findings demonstrated that EV owners in detached houses showed reduced interest in renting, while high-mileage drivers and those with daily charging needs exhibited increased willingness to participate. The research suggests that P2P-EVSE could particularly benefit multi-unit dwelling residents, addressing a known barrier to EV adoption. Higher adoption potential is predicted in regions like Southern California, where significant cost differences exist between home and public charging options.

Chapter 1 Introduction

Mass adoption of plug-in electric vehicles (EVs) remains a vital climate change mitigation tool in transportation sector decarbonization, as fuel-switching represents a less substantial structural change than alterations to transportation and land use activity and development (Rogelj et al., 2018). The global appetite for EVs is growing; 18% of all vehicles sold in 2024 were electric (IEA, 2024). By 2030, nearly one in five cars sold in the U.S. is expected to be electric, up from 10% in 2023, driven by improving cost parity, increasing consumer interest, and supportive government policies in both manufacturing and consumer purchasing (IEA, 2024). This anticipated growth partially relies on the development of a robust, convenient, and reliable public charging network capable of meeting both routine and non-routine charging needs—even if most charging continues to occur at home.

Public charging availability strongly influences EV adoption (Khaloei et al., 2020; Ledna et al., 2022), potentially exerting a stronger effect than socioeconomic factors and financial incentives (Sierzchula et al., 2014). To keep pace with globally announced EV adoption goals, the total number of public chargers must increase sixfold by 2035 from 2023 levels (IEA, 2024). In the U.S., a moderate growth scenario for EVs by 2030 would require at least 1 million publicly accessible Level 2 charging ports and 182,000 fast charging ports[1], primarily for long-distance trips (Wood et al., 2023). This represents a more than sevenfold increase in Level 2 chargers and nearly fourfold increase for fast chargers from current levels (U.S. DOE, 2024).

Globally, there is an average of 11 light-duty EVs per charger, though this ratio varies significantly across countries, reflecting differences in reliance on public charging infrastructure among early EV adopters (IEA, 2024). In the U.S. and European Union, a majority of early EV adopters benefit from home charging convenience. These users take advantage of extended overnight parking durations and more cost-effective residential electricity rates compared to commercial and industrial customers (Engel et al., 2018). Consequently, 50% to 80% of all EV charging events in the U.S. occur at home (Hardman et al., 2018). In contrast, China faces more challenges in home charging accessibility, resulting in over half of charging sessions taking place at public stations (Engel et al., 2018). This difference is reflected in the ratio of EVs per public charger: 26 in the U.S. compared to approximately 8 in China (IEA, 2024).

The limited availability of public charging infrastructure in the U.S. is partly by design, as early EVs adopters were predominantly single-family homeowners. However, this reliance on home charging creates a significant barrier for potential EV owners unable to install home chargers, who express a strong reluctance to purchase an EV (Dean and Kockelman, 2024). Even among early adopters, lack of home charging access has led to some EV abandonment. A study in California found that around 20% of EV drivers discontinued their EV ownership between 2012 and 2018, correlating strongly with the

[1] This study uses the term charger synonymously with electricity dispensing ports or connectors found on electric vehicle supply equipment (EVSE).

absence of home charging access, particularly Level 2 charging[2], and charging inconvenience (Hardman and Tal, 2021).

These findings suggest that aggressive EV adoption targets may be hindered without resolving home charging availability issues, and that public or workplace charging alone cannot address all charging needs. Additionally, there is growing concern about the reliability of public chargers, with up to 30% of U.S. public chargers offline at any given time (Rempel et al., 2023). This unreliability further exacerbates the challenges faced by EV owners without home charging options.

The challenges of home charging access are particularly pronounced in urban areas with high concentrations of multi-unit dwellings. By 2035, approximately one-fifth of EV owners in Los Angeles, America's most populous county, will lack at-home charging capabilities (Lee et al., 2023). While expanding public charging can address accessibility concerns, it does not resolve financial equity issues due to higher public charging costs. The average Los Angeles resident relying solely on public charging stations pays an additional 1% on their total household costs compared to those using home chargers. To mitigate this financial burden and encourage wider EV adoption, particularly among energy-burdened lower-income households, some researchers suggest implementing public charging subsidies or voucher programs (Vega-Perkins et al., 2023).

In response to these challenges, peer-to-peer residential charger sharing (P2P-EVSE) emerges as a compelling alternative. This innovative model allows owners of privately

[2] Level 2 EVSE can charge an EV up to eight times faster using a 240V power outlet (usually within 4 to 6 hours), compared to a Level 1 EVSE using a standard 120V outlet.

owned Level 2 charging stations to rent out charging access to nearby EV owners for specified time frames. **Error! Reference source not found.**.1 illustrates the transaction process, showcasing the interaction between renters, hosts, and the facilitating platform, which manages market access, enrollment, verification of charging sessions, and payment processing.

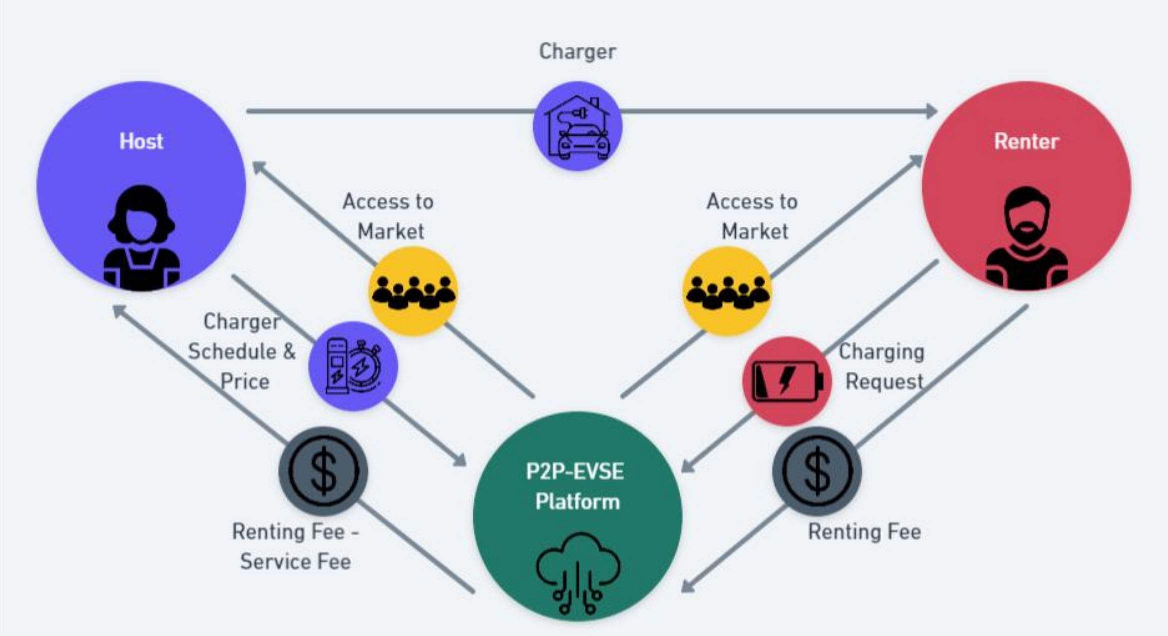

Figure 1.1: Illustration of peer-to-peer residential charger sharing (P2P-EVSE)

While the P2P-EVSE market is still in its infancy, several companies are already operating in this space across different regions. In the U.S., platforms such as EVmatch. Chargerzilla, Buzze, and GRIDSPOT have entered the market, while Europe has seen the emergence of Co Charger, Bookmycharge, and Zapmap.

P2P-EVSE offers several potential advantages over traditional public charging infrastructure:

1. *Rapid expansion of charging options:* By leveraging existing private chargers, P2P-EVSE can quickly augment the supply of publicly available charging infrastructure. In California, the U.S. state with the highest market share of EVs, there are 66,000 public and 87,000 shared private chargers, which are located at workplaces, multi-family residences, and other limited-access locations (California Energy Commission, 2024a). If just 15% of the state's more than 500,000 private chargers installed at residences were available on a P2P-EVSE platform, it would still exceed the total number of public chargers (California Energy Commission, 2024b).
2. *Cost-effectiveness:* It circumvents the upfront cost of purchasing and installing residential Level 2 chargers, which averages $1,800 (Borlaug et al., 2020).
3. *Improved reliability:* P2P-EVSE users can avoid challenges posed by unreliable public charging, such as faulty equipment, blocked access, or long queues (Rempel et al., 2023).
4. *Potential cost savings:* Public charging often incurs a markup of at least 37.5% compared to residential charging, depending on local electricity rates, congestion fees, and charging speed (Borlaug et al., 2020). If P2P-EVSE chargers are priced more competitively than public charging stations, they could help address social inequity in EV charging provisioning, as defined by Hopkins et al. (2023) as "an uneven opportunity for individuals or groups to benefit from electric vehicles due to the lack of provision, affordability or useability of charging infrastructure."

The large-scale implementation of P2P-EVSE could have far-reaching impacts on urban planning, energy grid management, and sustainable transportation policy by creating a more distributed and flexible charging network. Given these potential impacts and the pressing need for innovative charging solutions, it is crucial to study the P2P-EVSE concept in depth.

This thesis presents results from a web-based survey gauging the public's perception of this service, its opportunities, and barriers. The survey was designed to answer the following research questions:

1. Have people heard of peer-to-peer residential EV charger sharing (P2P-EVSE)?
2. What are the most important attributes of P2P-EVSE system to potential hosts and renters?
3. How far are potential P2P-EVSE users willing to walk to access a P2P-EVSE?
4. What are the greatest perceived benefits and risks of participating in P2P-EVSE?
5. Who is likely to become renters and hosts within a P2P-EVSE system?
6. What are the expected discounts for renters and markups for hosts in a P2P-EVSE system, and how do these expectations vary across different electric utility service areas?

The thesis has four key sections: a literature review of P2P-EVSE systems and the broader peer-to-peer (P2P) system, survey methodology and exploratory data analysis, model estimation and regression results, discussion of the paper’s contribution, and conclusions describing how these results shape P2P-EVSE's market potential.

Chapter 2 Literature Review

P2P-EVSE sharing operates within the broader sharing economy, where hosts and renters engage in co-consumption of goods and services. P2P exchanges vary in nature, interaction level, and transaction duration (Andersson et al., 2013). Examples include P2P house-sharing (Airbnb, Vrbo) and carsharing (Turo), which offer limited-time access to physical objects, typically arranged in advance. In contrast, ridesharing services (Uber, Lyft) provide short-lived and interactive services, often coordinated with limited advance notice. Recent technical advances in sensing and monitoring systems (Liu et al., 2023) have further enabled the growth of such sharing platforms by improving security and reliability.

2.1 Peer-to-Peer Charger Sharing Literature

Plenter et al. (2018) introduced the concept of P2P-EVSE platforms, conducting a web-based survey of electric utility account holders in Münster, Germany, to gauge acceptance of P2P-EVSE from the perspective of a host. With a 6.79% response rate (n = 437), they tested constructs for willingness to become hosts, yielding Cronbach's alpha values of 0.85 and 0.72 for intention to provide a P2P charger and available resources, respectively.

In a follow-up study, Plenter et al. (2018) used choice-based conjoint analysis to estimate willingness to pay for charging by location and speed. The study, with a 2.35% response rate (n = 470), found RFID cards as the preferred P2P authentication option, followed by smartphone apps and text messages.

P2P-EVSE may experience benefits and risks similar to other P2P platforms (Ballús-Armet et al., 2014). Benefits include reduced charging costs for EV drivers, increased host incomes, and potentially decreased demand for public charging infrastructure, which reduces the likelihood of queuing. However, P2P-EVSE may also encounter substantial challenges, including trust issues, charger availability, property access concerns, and potential property damage.

Liability is a crucial concern in the context of P2P-EVSE, as personal EVSE warranty policies generally do not cover non-standard uses, such as renting or leasing chargers to individuals other than the original purchaser (EVOCHARGE, 2024). Allowing others to access one's property and use the charger may elevate the risk of liability related to personal injury or accidents. Additionally, there is potential for damage to the renter's car due to faulty charging equipment, and conversely, a renter may cause damage to the charging equipment. Hosts assume potential damages and liabilities, with some incidents possibly covered by homeowner insurance or P2P-EVSE company policies[3] (Buzze, 2023; Chargerzilla, 2024; Co-charger, 2024). However, insurance companies may view P2P-EVSE as altering the host’s risk profile, potentially affecting premiums or policy renewals.

[3] Buzze provides up to $10,000 coverage for damage to the host’s charger or nearby property (Buzze, 2023).

2.2 Broader Peer-to-Peer Sharing Literature

Given the limited P2P-EVSE literature, insights from similar P2P sharing markets provide valuable context, as these may be transferable to P2P-EVSE. The following paragraphs highlight selected literature on peer-to-peer mobility sharing and accommodation sharing.

Jie et al. (2021) identified key determinants for using and adopting shared mobility options such as carpooling, ridesourcing, carsharing, and bike sharing in Western Australia. Their data from 220 residents indicated the importance of safety, convenience, timesaving, enjoyment attitudes, and the willingness to travel short distances to access shared mobility services. In the San Francisco Bay Area, Ballus-Armet et al. (2014) found low awareness but high willingness to share personal vehicles for P2P carsharing, despite liability concerns and trust issues.

Tussyadiah et al. (2016) explored satisfaction and intent to use P2P accommodation among U.S. travelers, identifying enjoyment, economic benefits (value), and accommodation amenities as positive factors, while surprisingly, sustainability had a small negative effect on satisfaction. These findings could transfer to P2P-EVSE, where factors like satisfaction, perceived benefits, and ease of use may impact user engagement. Similarly, distance to P2P-EVSE locations, personal security, and convenience may transfer from mobility-sharing services to shared chargers.

Accommodation-focused studies offer further insights. Lutz and Newlands (2018) highlighted the importance of privacy and social interaction in private versus shared accommodation choices, while Guttentag et al. (2018) segmented users by their motivations. These perspectives could help understand factors influencing EV owners' participation in P2P-EVSE platforms. Wang and Jeong (2018) found that personal innovativeness, perceived usefulness, and trust were key factors affecting platform attitudes, with host-guest relationships significantly impacting satisfaction. These insights could inform P2P-EVSE platform development, emphasizing practical benefits, trust-building, and positive interactions.

Tran and Filimonau's (2020) study on Airbnb adoption in Vietnam revealed differences from Western markets, with Vietnamese users prioritizing economic value and functional attributes over social benefits and unique experiences. This contrasts with Western studies that emphasize experiential factors in P2P service adoption (Lutz and Newlands, 2018). Personal security concerns and platform unfamiliarity emerged as primary demotivators, especially for non-users, highlighting the critical role of trust-building in new P2P markets (Ert et al., 2016; Möhlmann and Geissinger, 2018). These findings suggest that P2P-EVSE strategies in similar markets should focus on practical benefits, personal security, and familiarity rather than social or environmental aspects.

This thesis focuses on directly assessing user perceptions and potential behavioral changes in P2P-EVSE contexts. This paper explores practical aspects of P2P-EVSE acceptance, including awareness, perceived benefits and risks, and potential impacts on charging behavior, rather than testing a specific technology adoption framework. This approach aims to fill gaps in the existing literature by examining motivational factors and deterrents for both hosts and renters in P2P-EVSE systems, offering insights into the evolving landscape of peer-to-peer sharing and identifying opportunities and challenges for enhancing awareness and acceptance of these emerging platforms. Additionally, this thesis explores previously unexamined aspects of P2P-EVSE adoption, including users' walking distance preferences for accessing shared chargers and the economic dynamics of renter discounts and host markups across different electric utility service areas. By investigating these factors, the thesis provides a more comprehensive understanding of the potential for P2P-EVSE implementation and its regional variations, contributing valuable insights for policymakers, urban planners, and P2P-EVSE platform developers.

Chapter 3 Data & Methodology

3.1 Survey Design and Implementation

To investigate P2P-EVSE, we conducted an online survey from April to June 2024 using Prolific, a platform with pre-recruited research participants. Our target population was California residents who currently owned or leased a plug-in EV, either battery-electric (BEV) or plug-in hybrid electric (PHEV). We selected California as the study area due to its leading role in EV sales in the U.S. and its association with other tech-enabled P2P products, which we anticipated would help respondents grasp this new concept.

We initially collected 460 responses. After applying screening criteria and data quality checks (i.e., reviewing survey duration, identifying straight-lining responses, and checking for data inconsistencies)[4], we obtained a final sample of 367 responses. The average completion time was 17 minutes, with respondents compensated $10 for their participation.

[4] Screening criteria and data quality checks included: (1) attention check questions (e.g., instructing respondents to select a specific answer); (2) review of survey completion time, both overall and by section, to identify and remove abnormally fast responses; and (3) consistency checks across related demographic questions (e.g., comparing reported household composition with individual counts of adults, children, and workers) to ensure logical coherence in responses.

3.1.1 Survey Structure

The questionnaire was structured into several key sections:

- *Introduction and Informed Consent:* This section included screening questions and provided basic information about EVs to establish a common baseline of understanding.
- *Knowledge Questions:* We introduced the concept of the "Sharing Economy," differentiated between P2P sharing and business-to-customer models to lay the groundwork for discussing P2P-EVSE.
- *Socioeconomic Information:* Standard demographic data was collected to analyze how these factors might influence attitudes towards P2P-EVSE.
- *Household and Vehicle Information:* We gathered data on respondents' living situations and vehicle usage patterns to contextualize their expected charging needs and motivations regarding P2P-EVSE.
- *EV Charging Basics:* This section explored respondents' experiences with and attitudes towards range and charging anxiety. We introduced the concept of P2P-EVSE and gauged respondents' expectations about becoming renters or hosts in such a system.
- *Benefits and Risks of P2P-EVSE:* We delved into respondents' perceptions of the potential advantages and drawbacks of P2P-EVSE, exploring factors that might motivate or deter participation as hosts or renters.
- *Final Attitudes:* The survey concluded by assessing overall attitudes towards P2P-EVSE, capturing respondents' general disposition towards the concept.

It is important to note that our sample was not weighted to match broader population demographics, as our study focused specifically on California residents who own or lease EVs. While this limits the generalizability of our findings to the general population, it provides detailed insights into the perspectives of those most likely to engage in P2P residential charger sharing.

3.2 Analytical Methods

The data were analyzed using several complementary approaches: 1) descriptive summary statistics, 2) factor analysis and principal component analysis of attitudinal data, 3) binary logistic regression models estimating respondents' likelihood of participating in P2P-EVSE as hosts or renters, and 4) economic analysis of renter discounts and host markups.

Descriptive statistics illustrate the survey data's composition across various sub-populations (e.g., EV drivers with or without home charging access, home ownership, and housing type). Summary information reveals P2P-EVSE awareness, ranked benefits and risks for hosts and renters, and preferences for various P2P-EVSE app features.

Attitudinal data were analyzed using a two-step approach combining exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to identify key latent constructs influencing P2P-EVSE adoption. Additional attitudinal items were examined using Principal Component Analysis (PCA) to capture a comprehensive understanding of underlying attitudinal constructs.

To assess the willingness of EV drivers to become P2P-EVSE renters or hosts, we estimated two sets of binary logistic regression models—one set without attitudinal factors and another incorporating them. These models considered various socioeconomic, demographic, and behavioral variables, as well as the attitudinal factors derived from the factor analysis and PCA.

Finally, an economic analysis was conducted to examine the viability of P2P-EVSE adoption. This included assessing renter discount expectations and host markup expectations across different utility service territories in California. A sensitivity analysis comparing potential renter discounts and host markups against public and residential electricity rates evaluated the potential for successful matches between renters and hosts on P2P-EVSE platforms.

3.3 Respondent Summary Statistics

This study analyzed data from 367 California plug-in EV owners or lessees to understand their attitudes towards P2P-EVSE sharing. **Error! Reference source not found.** summarizes the respondent's demographic, household composition, residence, and vehicle variables from the complete data set. Respondents were categorized into two groups based on home charging capabilities: those with EV chargers at home (85.3%, n = 313) and those without (14.7%, n = 54). The latter group includes respondents who reported having an EV charger at home but never using it.

Table 3.1: Summary Statistics of Survey Responses

Explanatory Variables	**Sample**		
	No Home Charging (n = 54)	**Home Charging (n = 313)**	**Full Sample (n = 367)**
Gender (of respondent)			
Male	42.6	55.6	53.7
Female	55.6	43.8	45.5
Other/non-binary	1.8	0.6	0.8
Age (of respondent)			
18-24 years of age	16.7	23.3	22.3
25-34	57.4	36.1	39.2
35-44	11.1	22.4	20.7
45-54	9.3	9.9	9.8
55-64	3.7	4.5	4.4
65+	1.8	3.8	3.6
Highest level of education completed (of respondent)			
High school or less	3.7	4.5	4.4
Some college	11.1	25.5	23.4
Bachelor’s degree	63.0	47.0	49.3
Master’s degree or higher	22.2	23.0	22.9
Race (of respondent)			
White	35.2	43.1	42.0
Asian	40.7	35.5	36.2
Multiracial (two or more races)	14.8	9.9	10.6
Black	7.4	8.0	8.0
American Indian	1.9	1.6	1.6
Other/not disclosed	0.0	1.9	1.6
Hispanic status (of respondent)			
Hispanic	24.1	19.8	20.4
Not Hispanic	75.9	78.9	78.5
Prefer not to disclose	0.0	1.3	1.1
Household income, pre-tax (of respondent)			
Less than $30,000	7.4	1.9	2.7
Between $30,000 and $74,999	20.4	19.2	19.4

Between $75,000 and $99,999	14.8	17.6	17.2
Between $100,000 and $149,000	24.1	17.9	18.8
Between $150,000 and $199,000	14.8	15.3	15.3
Between $200,000 and $299,999	13.0	16.0	15.5
$300,000 and more	5.5	9.9	9.2
Prefer not to disclose	0.0	2.2	1.9
Employments status (of respondent)			
Employment, full time	64.8	60.4	61.0
Employment, part time	14.8	16.0	15.8
Student	14.8	15.0	15.0
Not employed/Searching for work	3.7	6.7	6.3
Other	1.9	1.9	1.9
Household size			
1 household member	14.8	7.7	8.7
2	38.9	21.1	23.7
3	13.0	23.6	22.1
4	22.2	32.6	31.1
5+	11.1	15.0	14.4
Residence type			
Single-family house (detached house)	38.9	75.4	70.0
4 or more-unit Apartments/condos	42.6	8.0	13.1
Townhouse (attached house)	5.5	9.9	9.3
2-3 Apartment/condos (buildings with only 2 to 3 dwelling units)	7.4	4.5	4.9
Mobile home/trailer	1.9	1.3	1.4
Dorm or retirement home/assisted care	0.0	0.3	0.3
Other	3.7	0.6	1.1
Residence status			
I own my home/apartment	18.5	49.5	45.0
I rent my home/apartment	63.0	21.4	27.5
I live with parents (or friends/others) and am not paying rent or Other	18.5	29.1	27.5
Level 1, level 2 awareness (of respondent)			
Yes, I was aware of Level 1 and Level 2 charging	64.8	73.5	72.2
No, I was not aware of Level 1 and Level 2 charging	35.2	26.5	27.8
P2P EV charging awareness (of respondent)			

Yes, I had heard of P2P EV charging	14.8	24.9	23.4
No, I had never heard of P2P EV charging	85.2	75.1	76.6
Range and charging anxiety (of respondent)			
Yes, I had heard of BOTH range anxiety and charging anxiety	50.0	49.5	49.6
Yes, I had heard of ONLY range anxiety	24.1	14.7	16.1
Yes, I had heard of ONLY charging anxiety	3.7	3.8	3.8
No, I had never heard of range anxiety and charging anxiety	22.2	32.0	30.5
EV charger type			
Level 1	NA	51.1	43.6
Level 2	NA	45.7	39.0
Fast Charging/Level 3	NA	3.2	2.7
Tesla owner/lessee			
Yes	7.4	49.8	43.6
No	92.6	50.2	56.4
Typical parking location of most frequently used vehicle (of respondent)			
Garage	24.1	37.1	47.7
Driveway	37.0	37.0	37.0
Shared garage/lot with controlled access (like a gate)	14.8	4.0	5.7
Shared garage/lot without controlled access	14.8	1.0	3.0
On the street/ or other location	9.3	6.1	6.5
Notes: NA = not applicable. The survey originally captured more detailed categories for “Highest level of education completed” (e.g., separate categories for high school, PhD, etc.) and “Household Income, pre-tax.” However, due to low response rates in some categories, these were combined in the final table for more meaningful analysis. For instance, PhD responses were grouped with “Master's degree or higher.” Similarly, some income brackets were consolidated. In the “Employment Status” category, “Other” includes individuals who are retired or unable to work due to disability. All values in the table are presented as percentages of the respective sample group.			

3.3.1 Demographic Characteristics

The sample was relatively balanced in gender (53.7% male, 45.5% female) and skewed younger, with 61.5% under 35 years old. This youth bias was more pronounced in the no-home-charging group (74.1% were under 35) compared to the home-charging group (59.4%). The sample was highly educated, with 72.7% holding at least a bachelor's degree.

Household income was relatively high, with 40.0% reporting annual incomes of $150,000 or more, with similar distributions between the home-charging and no-home-charging groups. The sample was racially diverse: 42.0% self-identifying as White, 8.0% Black, 36.2% Asian, and 10.6% Multiracial, with 20.4% identifying as Hispanic. The no-home-charging group had a higher proportion of Asian respondents (40.7%) compared to the home-charging group (35.5%).

3.3.2 Household and Residence Characteristics

The majority of respondents (61.0%) were employed full-time, with similar rates across both groups. Home-charging respondents tended to have larger households, with 71.2% living in households of three or more people, compared to 46.3% for those without home charging, suggesting housing type was associated with household size.

Housing conditions differed notably between groups. Among those with home charging, 75.4% lived in single-family detached houses, and 59.5% owned their homes. In contrast, only 38.9% of those without home charging lived in single-family homes, and 18.5% owned their residences. This difference likely reflects the challenges of installing home charging infrastructure in rental or multi-unit dwellings.

3.3.3 EV Charging Knowledge and Experience

Overall, 72.2% of respondents were aware of the distinction between Level 1 and Level 2 charging, with slightly higher awareness among those with home charging (73.5% vs. 64.8%). This suggests that experience with installing charging equipment may explain the higher awareness of different charging types. As expected, awareness of P2P-EVSE was lower among respondents without home charging (14.8%) compared to those with home charging (24.9%).

Among respondents with home charging access, there was no statistically significant difference between having Level 1 (51.1%) and Level 2 (45.7%) chargers. Only 3.2% reported having access to Fast Charging or Level 3 at home, which is consistent with the rarity of such high-powered charging in most residential settings.

Further analysis of home charging access reveals interesting charging and vehicle ownership patterns: among respondents without home charging access, 34% could access workplace chargers, providing an important alternative to public charging alone. Further, 70% of those without home charging own BEVs and 40% own PHEVs.

3.3.4 Range and Charging Anxiety Awareness

The survey assessed respondents' familiarity with range anxiety and charging anxiety, two common concerns among EV users. Key findings include:

- Overall, 69.5% were aware of at least one concept, with 49.6% familiar with both.
- Range anxiety was more widely recognized (16.1% aware of *only* this concept) compared to charging anxiety (3.8%).

- Those without home charging showed slightly higher awareness of range anxiety (24.1% vs. 14.7% for those with home charging).
- 30.5% had never heard of either concept, more prevalent among those with home charging (32.0% vs. 22.2%).

These findings provide important context for understanding EV owners' perceptions of potential challenges related to vehicle range and charging availability, which could influence their openness to alternative charging solutions like P2P EV charging.

3.4 Personal Attitudes Data Analysis

Research in P2P accommodation and mobility sharing highlights the importance of attitudes in predicting behavior. To explore this in the context of P2P-EVSE, our survey included 27 statements covering various aspects of respondents' attitudes, beliefs, and perceptions. These items addressed economic motivations, personal security (or safety) concerns, environmental consciousness, attitudes towards corporations and alternative economic systems, government policy support, general trust, technology adoption tendencies, social interactions, and privacy concerns.

Respondents indicated their level of agreement with each statement on a 5-point Likert-type scale, ranging from “Strongly Disagree” to “Strongly Agree.” These statements were designed to measure underlying latent constructs that might explain the observed intent to participate in P2P-EVSE platforms as hosts or renters.

3.4.1 Factor Analysis for Attitudinal Data

We employed a two-step approach, combining exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Initially, we used EFA, a data-driven approach commonly used to extract latent variables explaining observed behaviors without requiring theoretical hypotheses. This allowed us to establish the overall number of factors, identify items for each category, and explore correlations. Transportation researchers have previously used EFA to examine the adoption of new mobility services like ride-hailing (Malik et al., 2021). Following EFA, we conducted CFA to test our initial hypotheses when crafting the items used in the survey, refine the model, and ensure its practicality and realism. This combined approach allows us to determine key attitudinal dimensions influencing consumers' behavior and preferences in this emerging market while also validating our theoretical assumptions.

EFA aims to uncover latent variables (factors) that explain the observed correlations among a set of measured variables. This process involves:

3.4.2 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is a statistical technique used to identify underlying latent constructs that explain the observed relationships among a set of measured variables. It can be mathematically described as follows:

1. *Factor Model*

The EFA model assumes that each observed variable (X_i) is a linear combination of a set of latent factors (F_j) and a unique error term (E_i):

$$X_i = \lambda_{\{i1\}}F_1 + \lambda_{\{i2\}}F_2 + \ldots + \lambda_{\{ik\}}F_k + E_i,$$

where:

- X_i: Observed variable.
- F_j: Latent factors.
- $\lambda_{\{ij\}}$: Factor loading, representing the strength of the relationship between X_i and F_j.
- E_i: Unique error term specific to X_i.

2. Covariance Structure

The covariance matrix of observed variables (Σ) can be expressed as:

$$\Sigma = \Gamma\Gamma^T + \Psi,$$

where:

- Γ: Factor loading matrix.
- Ψ: Diagonal matrix of unique variances.

3. Factor Extraction

Factors are extracted using methods such as Principal Axis Factoring or Maximum Likelihood Estimation. These methods aim to maximize the variance explained by the factors.

4. Rotation

To enhance interpretability, rotation is applied to the factor loading matrix. Rotation methods include:

- Orthogonal (e.g., Varimax): Produces uncorrelated factors.
- Oblique (e.g., Promax): Allows for correlated factors.

5. Factor Retention

Decisions on the number of factors to retain are guided by criteria such as eigenvalues greater than 1 (Kaiser's criterion) and visual inspection of the scree plot.

3.4.3 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a theory-driven technique used to test the validity of hypothesized measurement models. CFA evaluates how well the observed data fit the proposed model through the following mathematical framework:

1. Measurement Model

The CFA model specifies the relationship between observed variables (y_i) and latent factors (η_j):

$$y_i = \lambda_{\{i1\}}\eta_1 + \lambda_{\{i2\}}\eta_2 + \ldots + \lambda_{\{ik\}}\eta_k + \epsilon_i,$$

where:

- y_i: Observed variable.

- η_1: Latent factors.
- $\lambda_{\{ij\}}$: Factor loading.
- ϵ_i: Measurement error.

2. Covariance Structure

The covariance matrix of observed variables is defined as:

$$\Sigma = \Lambda\Phi\Lambda^T + \Theta_\epsilon,$$

where:

- Λ : Factor loading matrix.
- Φ : Covariance matrix of latent factors.
- Θ_ϵ: Diagonal matrix of measurement errors.

3. Model Fit Assessment

CFA uses various fit indices to evaluate model adequacy:

- Chi-square test (χ^2): Tests the null hypothesis of perfect fit (sensitive to sample size).
- Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI): Values > 0.90 indicate acceptable fit.
- Root Mean Square Error of Approximation (RMSEA): Values < 0.08 suggest reasonable fit.

- Standardized Root Mean Square Residual (SRMR): Values < 0.08 indicate good fit.

4. Estimation Methods

Common methods include Maximum Likelihood Estimation (MLE) and its robust variations, which adjust for deviations from normality.

In this study, EFA was conducted to explore the underlying structure of attitudinal data without imposing theoretical constraints. The number of factors was determined based on eigenvalues and the scree plot, and rotation techniques were employed to improve interpretability. CFA was subsequently used to validate the measurement model derived from EFA and assess its goodness-of-fit using established indices. Together, these methods provided robust insights into the latent constructs influencing P2P-EVSE adoption.

Our analysis focused on a subset of items showing the strongest potential for revealing underlying constructs. The results, presented in Table 3.2, yielded a five-factor model capturing key dimensions related to P2P-EVSE adoption: Economic Motivation, Personal Security Concerns, Environmental Consciousness, Government Policy Support, and General Trust. Each factor comprises multiple measurement items, with factor loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE) reported for each construct.

The model's overall fit is satisfactory, as indicated by several goodness-of-fit indices. While the chi-square test (χ^2 (55) = 106.602, $p < 0.001$) is significant, which is common in large samples, other indices support the model's adequacy. The Robust Scaled

Comparative Fit Index (CFI) of 0.956 and Robust Scaled Tucker-Lewis Index (TLI) of 0.926 exceed the recommended threshold of 0.90, suggesting good fit (Hu and Bentler, 1999). It is worth noting that the non-robust standard CFI and TLI were even higher at 0.992 and 0.986, respectively. The Robust Scaled Root Mean Square Error of Approximation (RMSEA) of 0.076 (90% CI: 0.053–0.098) falls within the range of reasonable fit, and the Standardized Root Mean Square Residual (SRMR) of 0.050 is well below the recommended 0.08 cutoff.

Table 3.2: Assessment of the Measurement Model for P2P-EVSE Adoption

Constructs and related measurement items	Factor Loadings	Cronbach's Alpha	Composite Reliability	AVE
Economic Motivation		0.581	0.682	0.523
P2P sharing allows me to save money (as a renter).	0.606			
P2P sharing allows me to earn money (as a host).	0.824			
Personal Security Concerns		0.793	0.880	0.786
I don't feel safe walking alone in my neighborhood during the night.	0.916			
I don't feel safe walking alone in my neighborhood during the day.	0.856			
Environmental Consciousness		0.789	0.826	0.616
Consumers should change their behaviors to help solve the environmental challenges of today.	0.694			
I am committed to an environmentally-friendly lifestyle.	0.883			
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	0.765			
Government Policy Support		0.765	0.814	0.688
The government should raise the gas tax to help the environment.	0.903			
The government should raise vehicle registration fees on non-EVs to subsidize EV purchases.	0.749			

General Trust		0.627	0.708	0.550
Nowadays, you can trust anyone. *Originally reverse coded (negative)*	0.807			
I am convinced that most people have good intentions.	0.670			
χ^2 (55) = 106.602, $p < 0.001$ Observations = 367 Robust Scaled CFI = 0.956 Robust Scaled TLI = 0.926 Robust Scaled RMSEA = 0.076 (90% CI: 0.053–0.098) SRMR = 0.050				

The factor loadings in Table 3.2 reveal moderate to strong associations between measurement items and their corresponding latent constructs, ranging from 0.606 to 0.916. According to Comery and Lee's (1992) guidelines, these can be interpreted as good to excellent. Personal Security Concerns exhibit the highest loadings (0.916 and 0.856 for nighttime and daytime safety perceptions, respectively). Environmental Consciousness also shows robust loadings, with the highest (0.883) corresponding to commitment to an environmentally friendly lifestyle. Interestingly, the Economic Motivation construct shows a higher loading for earning money as a host (0.824) compared to saving money as a renter (0.606), suggesting profit potential may be more salient than cost savings. Government Policy Support demonstrates strong loadings for both items (0.903 and 0.749), while the General Trust construct displays moderate to strong loadings (0.670 and 0.807).

Reliability and validity assessments reveal Cronbach's Alpha values ranging from 0.581 to 0.793, with four out of five constructs exceeding the 0.7 threshold (Nunnally and Bernstein, 1994). The Personal Security Concerns construct demonstrates the highest reliability (α = 0.793), followed closely by Environmental Consciousness (α = 0.789) and Government Policy Support (α = 0.765). Composite Reliability values, which are less sensitive to the number of items, range from 0.682 to 0.880, with four constructs exceeding the commonly used threshold of 0.7 (Hair et al., 2010). AVE, a measure of convergent validity, ranges from 0.523 to 0.786, with all constructs exceeding the recommended threshold of 0.5 (Fornell and Larcker, 1981).

For the remaining attitudinal questions that did not perform well in the EFA, we conducted a Principal Component Analysis (PCA) to reduce dimensionality of remaining attitudinal items that could be extracted into a handful of moderately correlated main components. This additional analysis will be discussed in detail in the following section.

3.4.4 Principal Component Analysis for Attitudinal Data

In addition to the factor analysis approaches discussed earlier, we conducted a PCA on the remaining items. This approach aligns with the methodology employed by Alemi et al. (2019) in their study of factors influencing the adoption of on-demand ride services. By using both EFA and PCA, we aim to utilize all available data to capture a comprehensive understanding of the underlying attitudinal constructs that may influence P2P EV charger sharing behavior.

The rationale for employing PCA in this study stems from its ability to condense the dimensionality of attitudinal data without significant loss of information. This approach aligns with methodologies employed in behavioral research, such as Alemi et al. (2019), to explore latent constructs that influence decision-making. By applying PCA to attitudinal variables, we aim to uncover distinct, interpretable factors that influence peer-to-peer (P2P) electric vehicle (EV) charger sharing behavior.

Principal Component Analysis (PCA) is a fundamental dimensionality reduction technique widely employed in multivariate analysis to transform high-dimensional data into a lower-dimensional form while preserving maximum variance. In the context of attitudinal research, PCA serves as a powerful tool for identifying underlying patterns and structures in survey responses, enabling researchers to distill complex, multifaceted attitudes into interpretable components (Jolliffe and Cadima, 2016).

PCA operates by identifying orthogonal axes (principal components) that capture the directions of maximum variance in the data. Consider a dataset X with *n* observations and p variables, represented as an $n \times p$ matrix. The transformation begins by centering the data around its mean:

$$X_{centered} = X - \bar{X},$$

where $\bar{X}$ represents the mean vector of the variables.

The principal components are then derived from the eigendecomposition of the covariance matrix Σ:

$$\Sigma = \frac{1}{n-1} X_{centered}^{T} X_{centered}.$$

The eigendecomposition of Σ yields:

$$\Sigma = VDV^{T},$$

where V is a $p \times p$ matrix whose columns are the eigenvectors of Σ, and D is a diagonal matrix containing the corresponding eigenvalues $\lambda 1 \geq \lambda 2 \geq \ldots \geq \lambda p \geq 0$.

Each principal component PC_i is a linear combination of the original variables:

$$PC_i = X_{centered} v_i,$$

where v_i is the i-th eigenvector. The proportion of variance explained by each component is given by:

$$Proportion\ of\ Variance_i = \frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j}.$$

In the context of attitudinal research, special considerations must be made when applying PCA to Likert-scale or ordinal data. While PCA assumes continuous variables with normal distributions, research has shown its robustness in analyzing ordinal data when certain conditions are met (Cliff, 2014). The key considerations include:

1. Sample Size Adequacy: For attitudinal data, a minimum sample size of 5-10 observations per variable is recommended, with larger samples providing more stable solutions.

2. Scale Properties: Likert-scale items should demonstrate approximate interval properties and sufficient variance across response categories.

3. Correlation Structure: The presence of meaningful correlations between variables, as indicated by the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity, justifies the application of PCA.

The decision to retain components typically follows multiple criteria:

- Kaiser criterion: Retain components with eigenvalues > 1

- Scree plot examination: Identify the elbow point in the eigenvalue plot
- Cumulative variance explained: Retain components until a desired threshold (typically 60-80%) is reached
- Theoretical interpretability: Components should form meaningful constructs within the research context

This theoretical framework provides the foundation for our subsequent analysis of P2P EV charger sharing attitudes, where we employ PCA to identify distinct personality traits and beliefs that may influence adoption behavior.

Table 3.3: Principal component loadings in relation to P2P-EVSE adoption

Principal Components and Associated Variables	Loadings from Pattern Matrix	Eigenvalues (% of Variance)
Outgoing Individuals		15.2
I enjoy meeting new people with similar interests.	0.892	
Through P2P sharing, I can make nice acquaintances.	0.833	
Privacy-minded Individuals		14.8
It makes me uncomfortable ringing the doorbell of a stranger's house.	0.741	
I feel uncomfortable sharing my location with smartphone apps.	0.794	
My household uses blinds for privacy.	0.681	
Anti-Corporatism/Alternative Economy Supporters		14.3
P2P sharing allows me to not unnecessarily support large corporations.	0.905	
P2P sharing offers me an alternative to a capitalist system.	0.855	
P2P-EVSE Charging Policy Advocates		13.3
Instead of subsidies for public chargers, EV drivers should receive a one-time prepaid debit card to spend on charging (at public stations and P2P EV chargers).	0.833	
The government should pay P2P EV charger hosts for opening up their chargers to the public.	0.833	

Deal Seeking Individuals		11.9
As a consumer, I enjoy finding deals and bargains.	0.810	
I am a frugal person.	0.785	
χ^2 (10) = 323.34, $p < 0.001$ Observations = 367 RMSR = 0.09 Kaiser-Meyer-Olkin (KMO) Score: 0.64 Bartlett's test p-value < 0.001		

We performed PCA with an oblique (non-orthogonal) rotation (e.g., direct oblimin) on the remaining attitudinal items. The choice of oblique rotation was based on the likelihood of correlation between the factors under investigation. Given that our data pertains to social interactions, privacy concerns, and attitudes towards sharing and corporations, these constructs are likely to have some degree of correlation, making oblique rotation more appropriate for this analysis (Costello and Osborne, 2005).

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.64, which falls between Kaiser's (1970) definitions of good and superb (Field, 2012). Bartlett's Test of Sphericity yielded a p-value < 0.001, indicating that the correlations between items are sufficiently large for PCA (Field, 2012). The determinant of the correlation matrix was 0.120, which is larger than the threshold of 0.00001, supporting the suitability of our data for analysis and indicating no issues of multicollinearity or singularity.

As shown in Table 3.3, PCA resulted in five distinct personality traits or beliefs: outgoing individuals, privacy-minded individuals, anti-corporatism/alternative economy supporters, P2P-EVSE charging policy advocates, deal-seeking individuals. The component loadings for each item were robust, ranging from 0.681 to 0.905, indicating strong associations between the items and their respective components.

The outgoing individuals component reflects enjoyment of meeting new people and making acquaintances through P2P sharing, aligning with previous research on the importance of social aspects in collaborative consumption (Hamari et al., 2016). Privacy-minded individuals emerged as a distinct component, capturing discomfort with sharing personal information or space, identified as a potential barrier to P2P sharing in other contexts (Frenken and Schor, 2017). The anti-corporatism/alternative economy supporters component consolidates preferences for P2P sharing as an alternative to supporting large corporations or traditional business-to-consumer systems, echoing findings from studies on motivations for participation in the sharing economy (Böcker and Meelen, 2017). The P2P-EVSE charging policy advocates favor government subsidies that support and expand P2P charging infrastructure, similar to factors in broader EV adoption studies (Hardman et al., 2018). Lastly, deal-seeking individuals may be more willing to use P2P-EVSE if they believe it can lower charging costs as renters. This economic personality trait may even correlate with advocating for policy support, as identified in the context of other sustainable transportation solutions (Axsen and Kurani, 2013).

These PCA results complement our earlier EFA findings, providing a more comprehensive picture of the attitudinal factors that may influence P2P EV charger sharing behavior.

3.5 P2P-EVSE App Features: Host Preferences

Figure 3. illustrates the importance levels that current California EV drivers place on various host privileges as potential P2P-EVSE hosts, with results segmented by those

with and without home charging access. The results reveal key insights into user preferences and concerns.

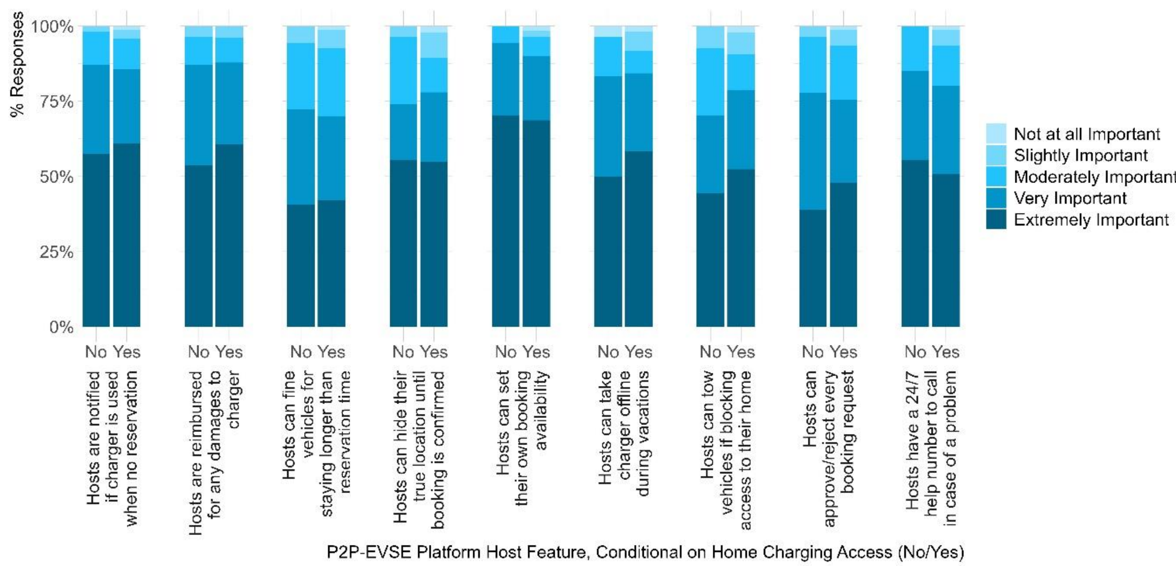

Figure 3.1: Importance of host features in a peer-to-peer EV charger sharing system (segmented by home charging access)

Reimbursement for charger damages emerges as a critical feature, with approximately 88% of both groups rating it as either “extremely important” or “very important.” This underscores the significance of financial protection and risk mitigation for potential hosts, regardless of their current charging setup. Control and flexibility are also highly valued. The ability to set booking availability schedules is a top priority, with over 90% of both groups considering this feature highly important. However, the ability to approve or reject booking requests is slightly less emphasized, with about 75–78% of respondents rating it as highly important. This desire for autonomy aligns with findings from other P2P systems like Airbnb, where Karlsson and Dolnicar (2016) found that hosts value controlling when and with whom they share their resources.

Privacy concerns are evident in the importance placed on hiding the host's true location until booking confirmation, particularly among those with home charging (approximately 78% rating it at least "very important"). This preference likely stems from security considerations associated with sharing personal property (Teubner and Flath, 2019).

Interestingly, those with home charging generally rate features as "extremely important" more frequently than those without, suggesting they may be more sensitive to potential risks associated with hosting. This indicates a potential gap may exist between stated and revealed preferences when it comes to host features on P2P-EVSE platforms: those with home charging equipment may be more protective since they have the equipment. Still, even the lowest-rated feature—the option to hide the host's true location until booking confirmation—is considered at least moderately important by over 89% of respondents with home charging access and over 96% of those without, indicating high overall expectations for app functionality and security measures.

These findings suggest that successful P2P-EVSE platforms will need to prioritize host protection, flexibility, and privacy to attract hosts. The strong preference for control over various hosting aspects indicates that a customizable approach may be more effective than a one-size-fits-all solution, allowing hosts to tailor their participation to individual needs and comfort levels.

3.6 Renter Perceptions of P2P-EVSE Risks and Benefits

Figures 3.2 and 3.3 illustrate the perceived importance of various risks and benefits associated with P2P-EVSE systems from the perspective of potential renters. This analysis highlights key insights into user preferences and concerns regarding P2P-EVSE adoption.

Liability-related concerns emerge as significant issues for potential renters. The risk of being liable for damage to one's own EV from faulty equipment is rated at least "very important" by over 77% of respondents. Similarly, liability for damage to the charger is a concern for approximately 63% of respondents who rate it as at least "very important." This highlights the critical need for clear liability policies and insurance coverage in P2P-EVSE platforms to address user concerns and facilitate adoption. Charger unreliability and the potential difficulty in finding a convenient charger are also major concerns. Over 80% of respondents rate charger unreliability as "very important" if not extremely important, while 69% are concerned about not finding a convenient charger. This emphasizes the importance of developing reliable charging networks and effective reservation systems to ensure availability.

While personal security concerns, such as intimidation or harassment by the host's neighbors, are considered important—with about 62% rating it at least "very important"—they are slightly less pressing than practical and financial risks. Concerns about leaving one's EV unattended and potential trespassing liabilities also garner attention but rank lower than issues of reliability and liability.

Turning to the benefits (Figure 3.3), convenience and monetary advantages are the most appealing aspects of P2P-EVSE platforms for renters. Approximately 87% rate having convenient and available nearby chargers as "very important," while about 70% emphasize monetary benefits. This suggests that P2P platforms should focus on expanding their networks and offering competitive pricing to attract users.

The expanded charging station options provided by P2P networks are highly valued, with over 62% of respondents considering this at least "very important." This reinforces the potential of P2P charging to complement existing public charging infrastructure and address accessibility concerns.

Notably, environmental benefits and reducing congestion at public charging stations are rated as less important compared to personal convenience and financial benefits. Only about 36% rate environmental benefits as at least "very important." This suggests that while sustainability is a factor, immediate practical advantages are more likely to drive P2P-EVSE adoption.

The relatively lower importance placed on not needing to install a home charger—approximately 38% rating it at least "very important"—suggests that many potential users still value the option of home charging, viewing P2P-EVSE as a supplement rather than a replacement for personal charging infrastructure.

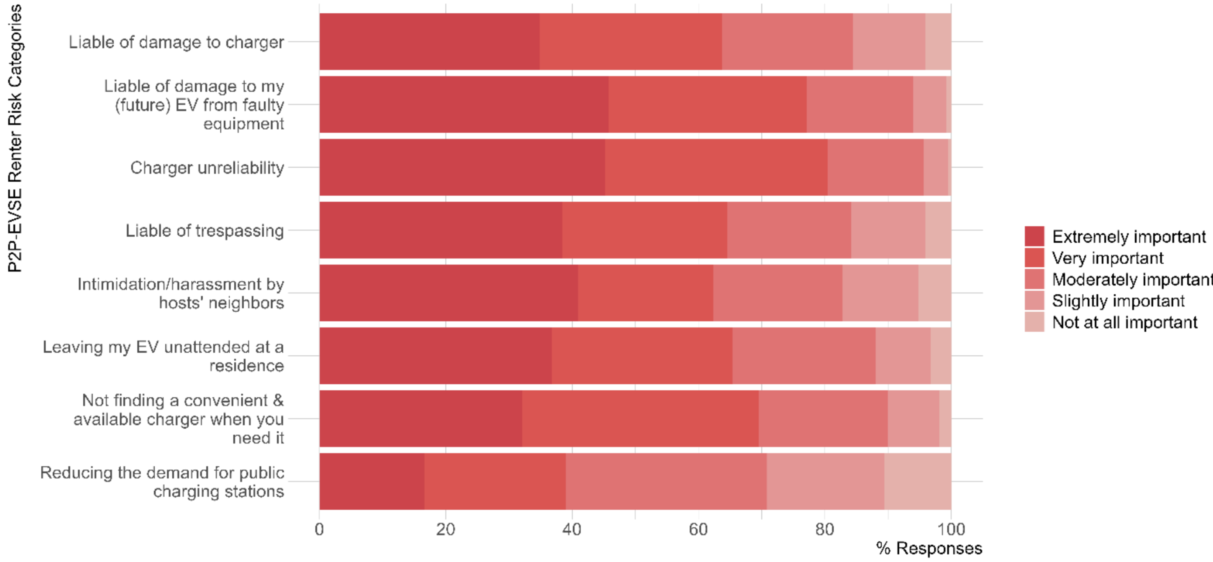

Figure 3.2: Perceptions of risks as a potential renter in peer-to-peer EV charger sharing

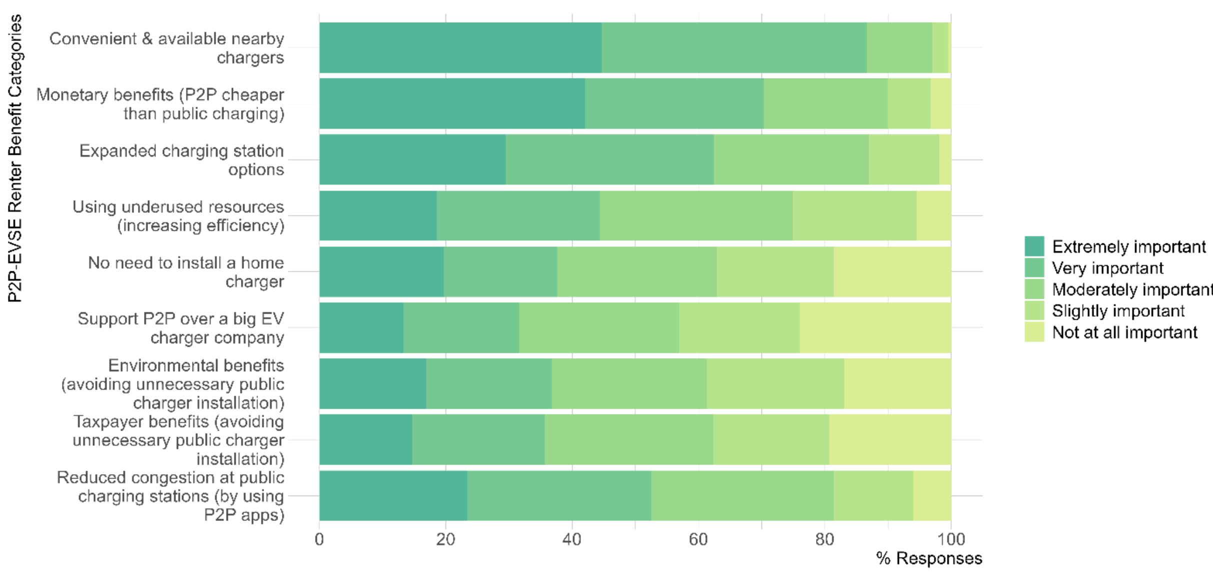

Figure 3.3: Perceptions of benefits as a potential renter in peer-to-peer EV charger sharing

3.7 Host Perceptions of P2P-EVSE Risks and Benefits

Figures 3.4 and 3.5 display the perceived importance of risks and benefits associated with P2P-EVSE from the perspective of potential hosts. Responses were separated between those with Level 2 chargers (38.7% of respondents) and can realistically become hosts, and those without (61.3%, including Level 1 charger owners). Those without home charging access or using Level 1 chargers were told to assume they had Level 2 chargers. The percentages presented are weighted averages, providing a comprehensive view of potential host perspectives.

Liability concerns and charger unreliability emerge as the most significant risks for potential hosts. Liability for damage to one's own charger is a top concern, with approximately 87% of respondents considering it at least "very important." This is closely followed by liability for damage to the renter's EV due to faulty equipment (about 81%) and liability for accidents with renters on the property (approximately 82.5%). Charger unreliability—defined as the inability to use one's own equipment due to damage from renting—is also a major issue, with around 86% rating it as at least "very important." These findings highlight the need for robust insurance policies and reliable equipment to mitigate hosts' concerns and encourage participation in P2P-EVSE platforms.

Personal security and safety also rank highly among potential hosts' concerns. About 81.8% rate leaving their residence unattended with unknown EV drivers accessing the property as at least "very important." Similarly, intimidation or harassment by EV drivers (approximately 67%) and negative interactions with EV drivers (about 70%) are significant concerns. These findings underscore the importance of implementing strong user verification systems and community management tools to build trust in P2P-EVSE.

Interestingly, while still important, time management stress (around 61.6%) and the potential reduction in demand for public charging stations (about 37%) are considered less critical risks compared to liability, reliability, and security concerns.

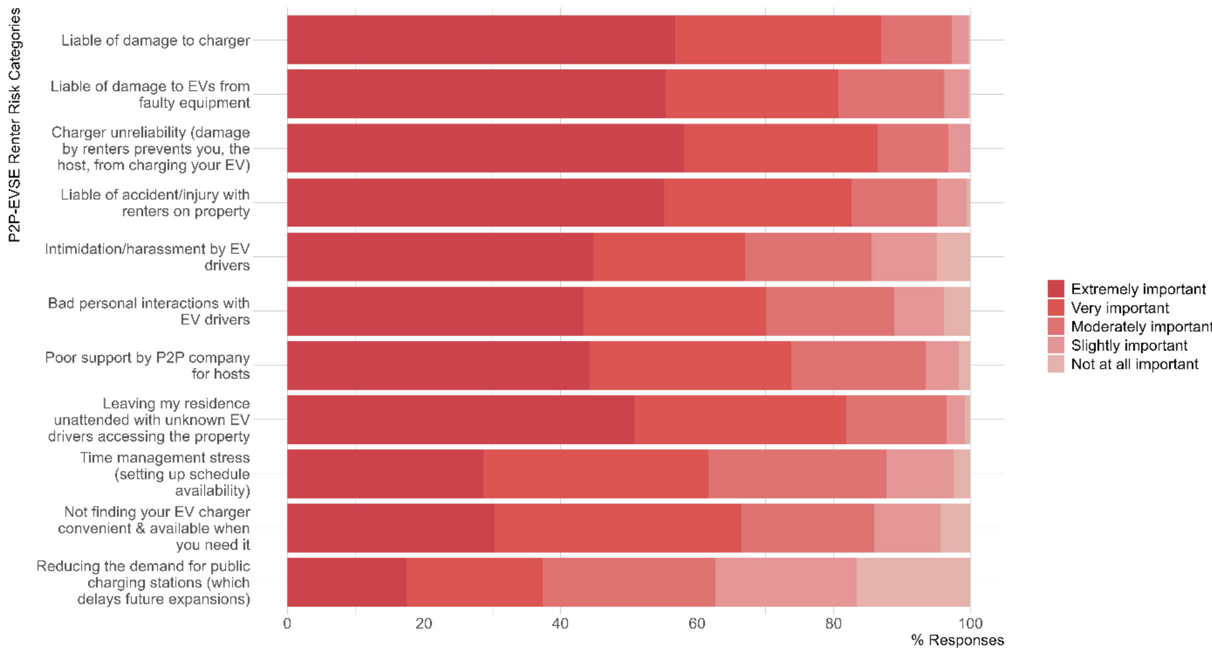

Figure 3.4: Perceptions of risks as a potential host in peer-to-peer EV charger sharing

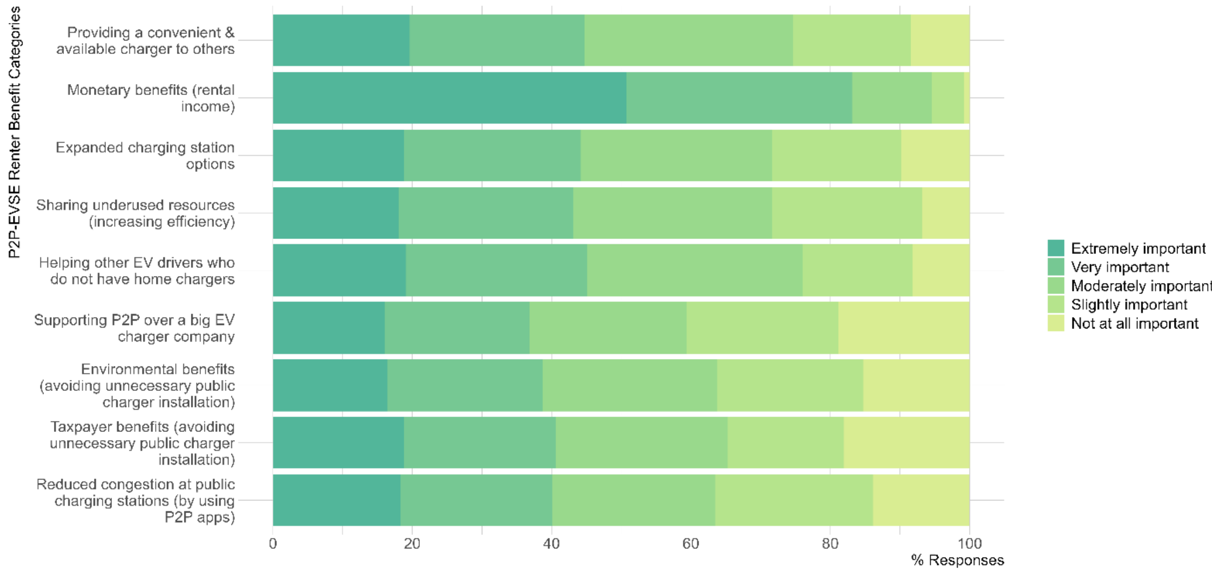

Figure 3.5: Perceptions of benefits as a potential host in peer-to-peer EV charger sharing

Turning to the benefits (Figure 3.5), monetary advantages clearly stand out as the most attractive aspect of hosting on a P2P-EVSE platform. An overwhelming 83% of respondents rate monetary benefits as at least "very important," significantly higher than any other benefit. This suggests that financial incentives will be a key driver in attracting hosts to P2P-EVSE platforms.

Other benefits are perceived as moderately important, with no clear standout after monetary benefits. Providing a convenient and available charger to others (approximately 45%), expanded charging station options (about 44%), and environmental benefits (around 38%) are all rated similarly in importance. This suggests that while these altruistic factors contribute to the overall appeal of P2P-EVSE, they are secondary to financial considerations for potential hosts. Notably, supporting P2P over a big EV charger company[5] is rated as less important (about 37% considering it at least "very important"), indicating that support for P2P systems may not be a significant motivator for most potential hosts.

3.8 Willingness to Walk to Access P2P-EVSE

This study examined potential renters' willingness to walk back to their residence after dropping off their EV at a P2P EV charger, assuming a fixed 4-hour charging time at a Level 2 charger. Respondents selected from a dropdown menu of one-way walking times, ranging from "within a 2 min walk (one-way)" to "over a 10 min walk (one-way) = over 1/2 mile."

Respondents showed a clear preference for shorter walking distances (Figure 3.6). The most common response (36.2%) was "within a 5 min walk (one-way) = 1/4 mile," closely followed by up to a 10 min walk (or ½ mile) (33%). A smaller portion (12.8%) said they would only walk up to 2 min for P2P-EVSE. While nearly half of potential renters prefer accessing a charger less than a 5 min walk away, 11.4% are willing to walk over 10 min one-way, prioritizing the benefits of P2P charging over any inconvenience of a longer walk. For these individuals, P2P charging could be integrated with existing routines, such as neighborhood walks, making longer distances less of an inconvenience if charger availability and session time align with their activities.

Notably, 6.5% indicated they "wouldn't walk" to use a P2P-EVSE charger, potentially representing non-adopters or those with mobility challenges. Overall, these preferences highlight the importance of near-home convenient charging access and integrating

[5] Readers may also know them by the technical phrase electric vehicle service providers (EVSPs).

charging with other activities, rather than treating it as a separate activity. As Hardman et al. (2018) emphasize, access to home and workplace charging is crucial for EV adoption.

Given the appeal for P2P-EVSE within 5 to 10 min walks, platforms can use walk catchment maps to target potential hosts. The strong preference for shorter walking distances suggests that a mix of residential tenure and housing types in neighborhoods may create opportunities for P2P-EVSE growth, as proximity is preferred, and later regression analyses indicate these variables are significant predictors for hosts and renters.

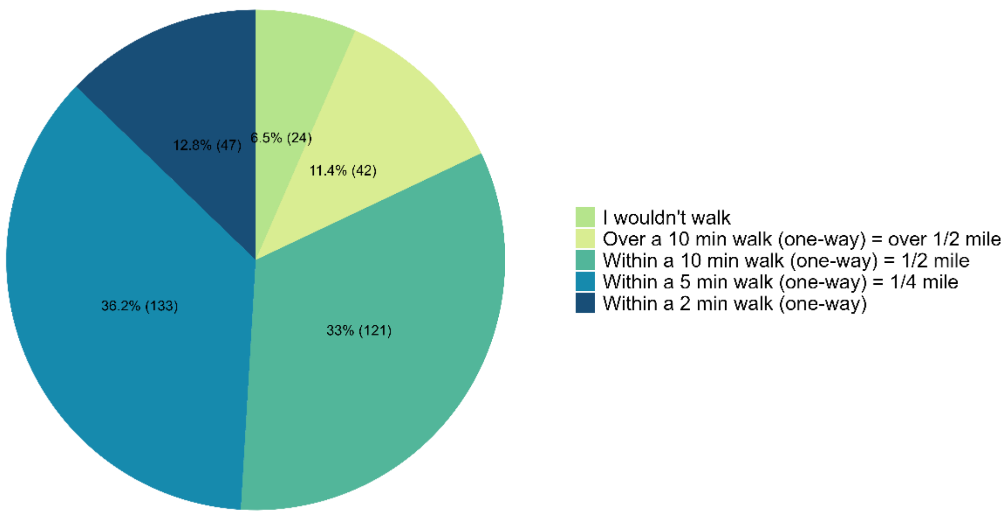

Figure 3.6: One-way walking preferences when accessing peer-to-peer EV charger sharing

Chapter 4 Results

4.1 Binary Logistic Regression: Theoretical Framework

Binary logistic regression (BLR) serves as a fundamental statistical method for modeling binary outcome variables, making it particularly suitable for analyzing adoption decisions in emerging technologies such as P2P-EVSE platforms. This section presents the theoretical foundation of BLR before proceeding to the specific model estimations for P2P-EVSE renters and hosts.

Mathematical Foundation

In BLR, we model the probability of a binary outcome (Y) conditional on a set of predictor variables (X). The logistic function transforms a linear combination of predictors into a probability bounded between 0 and 1:

$$P(Y=1|X)=\frac{e^{\beta_0+\beta_1X_1+\ldots+\beta_pX_p}}{1+e^{\beta_0+\beta_1X_1+\ldots+\beta_pX_p}},$$

where β_0 is the intercept and β_1 through β_p are the regression coefficients for p predictor variables. To simplify interpretation, we can transform the probability into the log-odds (logit) form:

$$logit\big(P(Y=1|X)\big)=\ln\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right)=\beta_0+\beta_1X_1+\ldots+\beta_pX_p$$

The odds ratio, a key interpretative measure, is obtained by exponentiating the coefficients:

$$Odds\ Ratio\ =\ e_i^{\beta}.$$

Model Estimation and Evaluation

The model parameters are estimated using maximum likelihood estimation (MLE), which maximizes the log-likelihood function:

$$\ln L(\beta) = \sum_{i=1}^{n}[y_i \ln(p_i) + (1 - y_i)\ln(1 - p_i)],$$

where n is the sample size, y_i is the observed outcome, p_i and is the predicted probability for observation i.

Model fit is assessed through several metrics:

1. *McFadden's Pseudo-R²:*

$$\frac{R^2_{McFadden} = 1 - \ln L(M_{Full})}{\ln L(M_{Null})},$$

where $L(M_{Full})$ is the likelihood of the fitted model and $L(M_{Null})$ is the likelihood of the null model.

2. *Information Criteria:*

Akaike Information Criterion (AIC):

$$AIC\ =\ -2ln\ L\ +\ 2k$$

Bayesian Information Criterion (BIC):

$$BIC = -2 \ln L + k \ln(n)$$

This theoretical framework provides the foundation for the subsequent analyses of P2P-EVSE renter and host adoption patterns presented in Sections 4.2 and 4.3.

4.2 Model Estimation: Who is Likely to Rent in P2P-EVSE Platforms?

This study employed two binary logistic regression (BLR) models to examine factors influencing the likelihood of becoming a P2P-EVSE renter: a base model and an extended model that included attitudinal factors (Table 4.1).

The results indicate that non-White and non-Asian Americans demonstrated higher likelihood of becoming renters, with this effect being significant in both models (without attitudes: $\beta = 1.41$, $p < 0.01$; with attitudes: $\beta = 1.02$, $p = 0.02$). This finding aligns with previous research in the broader sharing economy context. Davidson et al. (2018) found that racial minorities were more likely to participate in P2P carsharing platforms, potentially due to economic considerations and greater need for flexible transportation options. In the P2P-EVSE context, this pattern may reflect disparities in charging infrastructure access across disadvantaged communities (Hsu and Fingerman, 2021). Notably, the effect of racial minority status on P2P-EVSE renter acceptance was tempered for Tesla owners (without attitudes: $\beta = -1.24$, $p = 0.02$; with attitudes: $\beta = -1.22$, $p = 0.03$), though remaining positive overall. This moderation effect might be attributed to Tesla's extensive proprietary charging network, which could reduce Tesla owners' reliance on alternative charging solutions.

Table 4.1: Binary Logistic Model With and Without Attitudes For Renters

Variables	Without attitudes				With attitudes			
	Coef.	**Odds Ratio**	**95% CI**	**p-value**	**Coef.**	**Odds Ratio**	**95% CI**	**p-value**
Intercept	-1.58	0.21	(0.11 – 0.37)	<0.01	-1.34	0.26	(0.14 – 0.47)	<0.01
Socioeconomic Factors								
PHEV Owner (Binary)	0.90	2.48	(1.50 – 4.16)	<0.01	0.91	2.48	(1.47 – 4.24)	<0.01
Race: Non-White & Non-Asian American	1.41	4.08	(1.87 – 9.24)	<0.01	1.02	2.78	(1.19 – 6.67)	0.02
Non-White & Non-Asian American × Tesla Owners	-1.24	0.29	(0.09 – 0.83)	0.02	-1.22	0.29	(0.09 – 0.89)	0.03
Residence Type: Detached house	-0.58	0.56	(0.33 – 0.95)	0.03	-0.69	0.50	(0.29 – 0.87)	0.01
Travel Mode in Last Month: Electric scooter (e-scooter) or Biking (including e-bikes)	0.69	1.99	(1.11 – 3.57)	0.02	NA	NA	NA	NA
Typical Weekly Mileage: 250-399 Miles	0.69	1.99	(0.96 – 4.10)	0.06	0.88	2.40	(1.13 – 5.12)	0.02
Frequency of Charging for Routine Trips: At least once a week	0.51	1.67	(0.95 – 2.90)	0.07	0.54	1.71	(0.96 – 3.04)	0.06
Charging Anxiety: Strongly agree	1.05	2.85	(1.47 – 5.55)	<0.01	1.07	2.92	(1.47 – 5.83)	<0.01
Walking Distance to P2P EVSE Charger: I would not walk	-3.25	0.04	(0.00 – 0.22)	<0.01	-3.31	0.04	(0.00 – 0.22)	<0.01

P2P EVSE Impact on Charging Anxiety: Much lower	0.64	1.88	(0.96 – 3.70)	0.05	0.62	1.86	(0.92 – 3.75)	0.08
Attitudinal Factors§								
Outgoing Individuals	NA	NA	NA	NA	0.49	1.63	(1.25 – 2.16)	<0.01
P2P-EVSE Charging Policy Advocates	NA	NA	NA	NA	0.36	1.43	(1.08 – 1.91)	0.01
Model Specification								
Log-likelihood (model)	-189.28				-180.72			
Degrees of freedom	11				12			
AIC	400.56				385.44			
BIC	443.52				432.30			
Observations	367				367			
McFadden pseudo-R^2	0.17				0.21			
Dependent variable is 1 = Becoming a Renter, 0 = Not Becoming a Renter								
Note: RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; NA = Not Applicable.								
§ Note that the statements associated with these factor scores are measured on a five-point Likert-type scale from “Strongly disagree” to “Strongly agree.”								

PHEV owners were 2.48 times more likely to become renters, potentially due to their vehicles' dual-fuel nature and reliance on charging for short-range trips. This finding suggests that PHEV owners may view P2P-EVSE as a practical solution for extending their electric range without full dependence on public charging infrastructure, consistent with research by Axsen and Kurani (2013) showing more diverse charging behaviors among PHEV owners compared to BEV owners. Residents of detached houses showed 50% lower odds of becoming renters in the attitudinal model, likely due to their greater access to home charging solutions (Hardman et al., 2018). No statistically significant interaction effect was observed between PHEV ownership and detached housing types.

EV drivers with higher weekly mileage (250-399 miles, above the national average) showed increased likelihood of becoming renters, with this effect strengthening in the attitudinal model. This finding highlights the importance of charging convenience for frequent EV users with above-average mobility needs. Similarly, frequent charging behavior (minimum once weekly) positively correlated with renter likelihood, emphasizing P2P-EVSE's role in expanding charging options.

Participants reporting strong charging anxiety exhibited 2.92 times higher odds of becoming P2P-EVSE renters in the attitudinal model ($\beta = 1.07$, $p < 0.01$). This aligns with findings from Bonges and Lusk (2016) that range anxiety, closely related to charging anxiety, significantly impacts EV adoption. P2P-EVSE may serve as a strategy to address range anxiety, potentially mitigating its negative effect on EV adoption decisions.

Individuals unwilling to walk to P2P-EVSE locations showed significantly lower likelihood of becoming renters (96% lower odds in both models). This finding parallels carsharing adoption studies where proximity to shared vehicles substantially influenced usage patterns (Kortum, 2012)

The inclusion of attitudinal factors provided additional insights. Outgoing individuals demonstrated higher renter likelihood, with each unit increase in lifestyle score associated with 1.63 times higher odds of participation. This suggests that individuals valuing social aspects of sharing economy platforms are more inclined to participate in P2P-EVSE as renters, aligning with Möhlmann's (2015) identification of community belonging as a significant factor in carsharing service use.

Advocates of P2P-EVSE charging policy, particularly subsidies, showed an increased likelihood of becoming renters. This association between policy support and willingness to participate in innovative charging solutions suggests potential synergies between policy attitudes and adoption behavior.

The negative intercept in both BLR models indicates a baseline reluctance toward P2P-EVSE renter participation, potentially stemming from concept unfamiliarity, reliability concerns, or preference for established charging options. As Malhotra and Van Alstyne (2014) discuss, trust issues, privacy concerns, and uncertainty can create initial adoption barriers in P2P markets, potentially explaining this baseline reluctance.

The models' The McFadden pseudo-R^2 values indicate that the attitudinal model (0.21) explains more variance in the dependent variable compared to the base model (0.17). While these values suggest moderate fit, they are acceptable for logistic regression models using stated preference survey data. The inclusion of attitudinal factors enhances our understanding of the determinants influencing P2P-EVSE renter likelihood.

4.3 Model Estimation: Who is Likely to Host in P2P-EVSE Platforms?

Similar to the renter analysis, this study estimated two BLR models to examine factors influencing P2P-EVSE host likelihood: a base model and an extended model incorporating attitudinal factors (Table 4.2). The analysis focused exclusively on respondents who reported any home charging access in their households.

Household size emerged as a significant predictor, with larger households showing greater likelihood of becoming hosts (without attitudes: β = 0.30, $p < 0.01$; with attitudes: β = 0.23, $p = 0.05$). Each additional household member increased hosting odds by 35% in the base model and 26% in the attitudinal model. This finding aligns with broader sharing economy research, where Böcker and Meelen (2017) found higher participation rates among larger households, potentially due to greater resource availability and diverse household needs.

Table 4.2: Binary Logistic Model With and Without Attitudes For Hosts

Variables	**Without attitudes**				**With attitudes**			
	Coef.	**Odds Ratio**	**95% CI**	**p-value**	**Coef.**	**Odds Ratio**	**95% CI**	**p-value**
Intercept	-1.67	0.19	(0.08 – 0.43)	<0.01	-1.30	0.27	(0.11 – 0.64)	<0.01
Socioeconomic Factors								
Household Size	0.30	1.35	(1.09 – 1.68)	<0.01	0.23	1.26	(1.00 – 1.58)	0.05
Residence Type: Detached house	-0.98	0.38	(0.18 – 0.79)	<0.01	-0.94	0.39	(0.18 – 0.85)	0.02
Detached house × Homeowners	0.83	2.28	(1.20 – 4.34)	0.01	0.76	2.15	(1.10 – 4.27)	0.03
Travel Mode in Last Month: Electric scooter (e-scooter) or Biking (including e-bikes)	0.94	2.55	(1.41 – 4.64)	<0.01	0.81	2.25	(1.21 – 4.18)	<0.01
Typical Parking location for the EV driving the most: Garage	-1.41	0.24	(0.08 – 0.60)	<0.01	-1.65	0.19	(0.06 – 0.51)	<0.01

Typical Parking location for the EV driving the most: Garage × Full-time worker	1.59	4.89	(1.95 – 14.18)	<0.01	1.56	4.78	(1.80 – 14.67)	<0.01
Frequency of Charging for Routine Trips: At least once a week	0.77	2.16	(1.18 – 3.95)	0.01	NA	NA	NA	NA
Attitudinal Factors [§]								
Economic Motivation	NA	NA	NA	NA	0.18	1.22	(1.03 – 1.40)	0.02
Outgoing Individuals	NA	NA	NA	NA	0.34	1.40	(1.05 – 1.91)	0.02
P2P-EVSE Charging Policy Advocates	NA	NA	NA	NA	0.35	4.44	(1.07 – 1.90)	0.02
Model Specification								
Log-likelihood (model)	-172.87				-162.66			
Degrees of freedom	8				10			
AIC	361.73				345.31			
BIC	391.70				382.78			
Observations	313				313			
McFadden pseudo-R^2	0.13				0.18			
Dependent variable is 1 = Becoming a Host, 0 = Not Becoming a Host								
Note: RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; NA = Not Applicable.								
[§] Note that the statements associated with these factor scores are measured on a five-point Likert-type scale from “Strongly disagree” to “Strongly agree.”								

Housing type significantly influenced hosting likelihood, with detached house residents showing lower propensity to become hosts across both models (without attitudes: β = -0.98, p < 0.01; with attitudes: β = -0.94, p = 0.02). However, this effect was moderated by home ownership status. While the baseline coefficient for detached house residents was -0.98, the net effect for homeowners in detached houses was substantially less negative

(-0.15 = -0.98+0.83). This suggests that ownership status significantly influences P2P-EVSE hosting decisions, possibly because homeowners have greater autonomy in installing and sharing charging infrastructure, consistent with prior sharing economy research (Li et al., 2016; Wegmann and Jiao, 2017).

Regular users of electric scooters and bicycles (including e-bikes) demonstrated a significantly higher likelihood of becoming P2P-EVSE hosts. These users showed 2.55 and 2.25 times higher odds of becoming hosts in the base and attitudinal models, respectively. This suggests that individuals already engaged with sustainable and shared mobility options may demonstrate greater openness to P2P-EVSE hosting, supporting findings by Shaheen et al. (2020) regarding multi-modal shared mobility users' openness to new transportation technologies.

Private garage parking of the primary EV (compared to driveways, streets, or other locations) decreased hosting likelihood, potentially due to concerns about garage access or blocking egress to the garage. However, this effect was moderated by employment status. In the base model, full-time workers parking in private garages showed a slight positive association with hosting (+0.18 = -1.41+1.59). This relationship became negative in the attitudinal model when controlling for factors such as economic motivation, outgoing individuals, and policy support for P2P-EVSE.

The attitudinal model revealed additional insights even while the direction of impacts is mostly as expected. In particular, individuals with stronger economic motivations are more likely to become hosts, with each unit increase in economic motivation associated with 1.22 times higher odds of becoming a host. This aligns with Böcker and Meelen's (2017) identification of economic factors as primary drivers of P2P service participation, particularly in mobility contexts. Similarly, outgoing individuals showed increased hosting likelihood, with each unit increase in this score associated with 1.40 times higher hosting odds. This suggests that individuals valuing social aspects of sharing platforms are more inclined toward P2P-EVSE hosting, consistent with Möhlmann's (2015) findings in carsharing contexts. Additionally, supporters of government subsidies for P2P-EVSE platforms demonstrated higher hosting odds, indicating potential alignment between policy preferences and participation willingness.

Both models revealed negative intercepts, suggesting an underlying reluctance toward P2P-EVSE hosting. This baseline hesitation may stem from property damage concerns, liability considerations, or preferences for private charging infrastructure use. As Malhotra and Van Alstyne (2014) note, trust issues and uncertainty often create initial participation barriers in P2P markets, potentially explaining this baseline reluctance.

4.4 Economic Analysis: Renter Discount and Host Markup

To understand the economic motivations of potential P2P-EVSE participants, we examined expected discounts (for renters) and markups (for hosts) that would drive platform acceptance. Renters indicated their minimum acceptable discount compared to public charging rates that would motivate them to use P2P-EVSE, with options ranging from 0% to 50%. This upper limit was implemented to ensure realistic assessment of user expectations. Hosts specified their minimum acceptable markup, ranging from 0% to 100%. Table 4.3 presents these preferences segmented by home charging capability.

Table 4.3 Summary Statistics for the Stated Minimum Renter Discount and Host Markup for Accepting Peer-to-Peer Charging Platforms

Data Statistic	**Renter Discount (in %)**		**Host Markup (in %)**	
	No EV Charger/ Level 1) (*n = 54*)	Level 2 EV Charger (*n = 313*)	No EV Charger/ Level 1) (*n = 54*)	Level 2 EV Charger (*n = 313*)
Mean	28.31%	27.76%	33.51%	41.35%
Median	27.00%	25.00%	30.00%	40.00%
Standard Deviation	12.50%	13.25%	26.20%	24.38%
Minimum	5.00%	0.00%	3.00%	5.00%
Maximum	50.00%	50.00%	100.00%	100.00%

Table 4.3 statistics reveal similar discount expectations between respondents with and without Level 2 chargers when deciding to become renters (means of 27.76% and 28.31%, respectively). The Mann-Whitney U test indicated no significant association between Level 2 home charging capability and the minimum required P2P-EVSE rental discount ($U = 8702.0$, $p = 0.725$). This consistency may partly reflect respondent behavior with slider scales, where participants often gravitate toward central values (approximately 25%) before adjusting (Weijters et al., 2010).

However, markup expectations differed significantly between potential hosts with and without Level 2 EV chargers (Mann-Whitney U test: $U = 6500.0$, $p < 0.01$). Level 2 charger owners expected higher markups (mean: 41.35%) compared to non-owners (mean: 33.51%). This disparity may reflect several factors:

1. Investment recovery: Level 2 charger owners may factor in the cost of their initial equipment costs, seeking higher returns to offset this sunk expense.

2. Perceived value: Direct home charging experience may increase owners' value assessment of their equipment, leading to higher price expectations (i.e., “I place a higher value for this, therefore my customers ought to.”).
3. Risk perception: Owners may better understand potential risks (e.g., wear-and-tear, liability) and seek compensatory premiums.
4. Opportunity cost: Owners may place higher value relinquishing access to personal charging equipment and space, such as driveways.

The gap between renters' discount expectations (approximately 28%) and hosts' markup expectations (approximately 40% overall) could present adoption barriers. To assess the feasibility of meeting both parties' expectations while maintaining competitiveness with public charging options, we analyzed California's public charging and residential electricity rates.

To examine regional variations in pricing expectations, we mapped respondents to California's major Investor-Owned Utilities (IOUs). Of 367 respondents, 303 were successfully mapped to service areas of Pacific Gas and Electric (PG&E), Southern California Edison (SCE), or San Diego Gas & Electric (SDG&E). These IOUs serve approximately 75% of California's electricity customers (CPUC, 2020). Our classification did not distinguish between customers directly served by these IOUs and those served by small municipally-owned utilities (MOUs) or community choice aggregators (CCAs). In other words, we assumed a bundled generation and delivery rate provided by these three IOUs. This approach allowed us to capture a significant portion of our sample while simplifying the diverse landscape of California's retail electricity market.

We employed Kernel Density Estimation (KDE) to visualize the distribution of pricing expectations across utility service areas. KDE is a non-parametric method for estimating the probability density function of a continuous random variable, allowing us to smooth out the data and identify underlying patterns. Figure 4.1 presents renter discount expectations for the three IOUs, with a 50% threshold marked by a vertical red line. Likewise, Figure 4.2 shows host markup expectations. The KDE curves for renter discounts peak around 20%-30% across all utilities, consistent with our aggregate findings. Host markup expectations showed greater variation (as shown in Table 4.3), with PG&E customers demonstrating more concentrated lower markup expectations compared to SCE and SDG&E customers.

SCE and SDG&E customers exhibited similar distribution patterns for both hosting and renting, suggesting shared expectations among Southern California respondents. This alignment may reflect geographical proximity and similar socioeconomic or electricity pricing conditions. Conversely, PG&E customers, primarily in Northern and Central California, showed distinct patterns, potentially reflecting regional variations in electricity rates, charging infrastructure availability, or other market factors.

These regional differences suggest the potential value of broader Northern/Southern California categorization in future analyses, which could inform region-specific P2P-EVSE implementation strategies and pricing policies. The findings highlight the importance of considering local electricity market conditions and consumer behavior patterns when developing P2P-EVSE platforms and related policies.

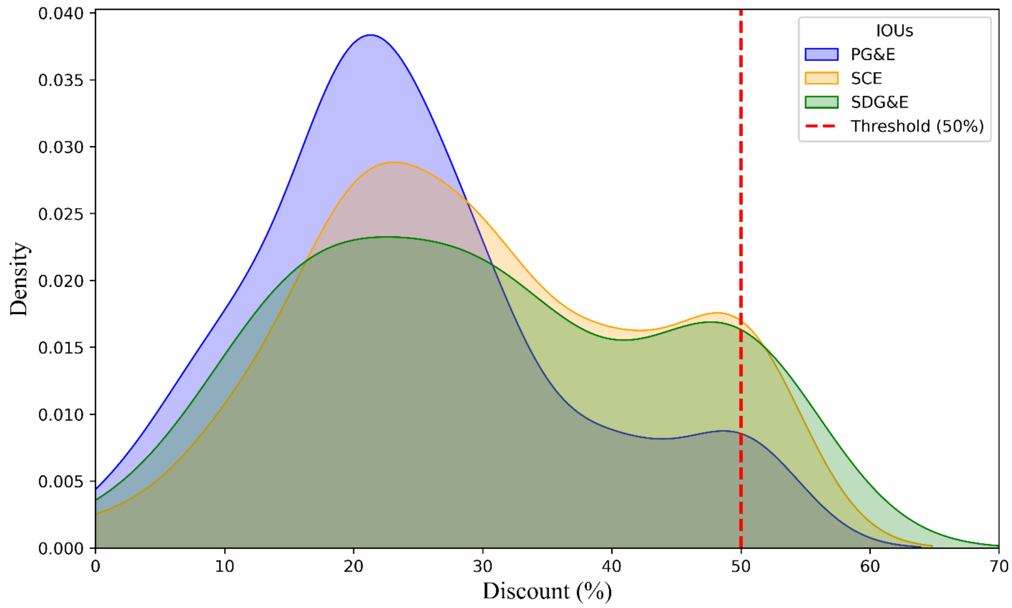

Figure 4.1: Kernel density plots of the respondent's discount expectations as a renter by their electric utility

Note: The 50% discount threshold displayed in a dotted red line is the upper bound on censored data. Respondents answering 50% may have desired an unobserved higher value.

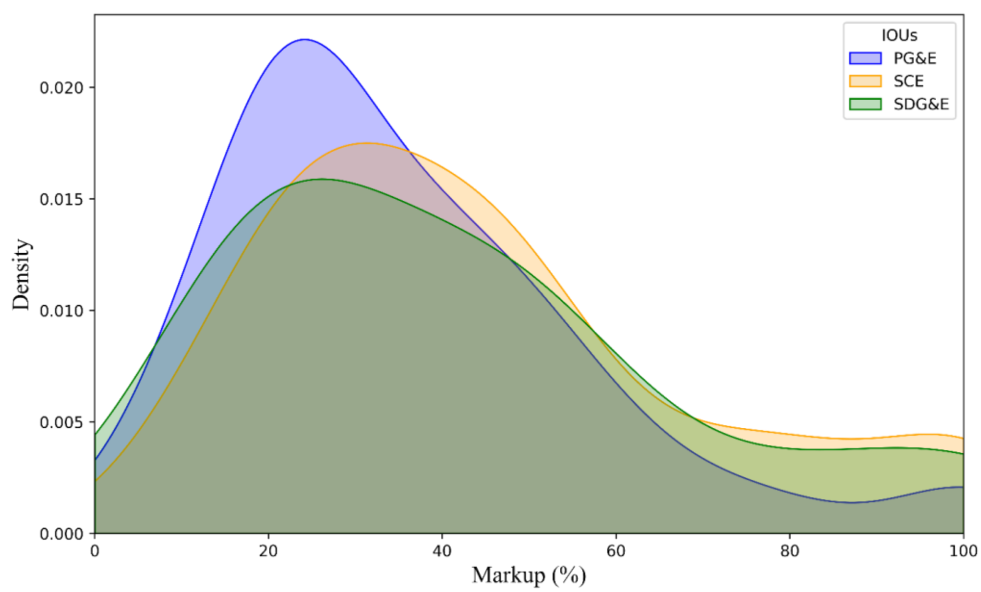

Figure 4.2: Kernel density plots of the respondent's markup expectations as a host by their electric utility

To examine regional variations in pricing expectations across utility service areas (PG&E, SCE, and SDG&E), we conducted non-parametric statistical tests, given the potentially non-normal distribution suggested by our density plots.

We first applied the Kruskal-Wallis H Test, a non-parametric alternative to one-way ANOVA (Kruskal and Wallis, 1952), to assess differences among the three groups for both renter discount and host markup expectations. The results are presented in Table 4.4.

The Kruskal-Wallis H Test revealed statistically significant differences across utility service areas for both renter discount expectations ($H = 14.23$, $p < 0.001$) and host markup expectations ($H = 8.45$, $p = 0.013$). These findings confirm meaningful regional variations in P2P-EVSE pricing expectations throughout California, particularly for renter discounts. To identify specific regional differences, we conducted post-hoc Dunn Tests with Bonferroni correction for multiple comparisons (Dunn, 1961).

For renter discount expectations, post-hoc tests revealed significant differences between PG&E and SCE ($p < 0.001$) and between PG&E and SDG&E ($p = 0.07$), while SCE and SDG&E showed no significant difference. This aligns with our density plot observations, suggesting shared expectations among SCE and SDG&E customers. Regarding host markup expectations, only the difference between PG&E and SCE proved significant ($p = 0.01$), with no statistically significant difference between PG&E and SDG&E or between SCE and SDG&E.

These results support the hypothesis of distinct regional differences between Northern California (PG&E) and Southern California (SCE and SDG&E combined) in stated discount and markup preferences. While Southern California utility territories showed larger host markups than Northern California, this regional gap was less pronounced than that observed in renter discounts.

Table 4.4: Results of Statistical Tests for P2P-EVSE Pricing and Electric Utility Service Areas

Statistical Tests and Values	Renter Discount	Host Markup
Kruskal-Wallis H Test		
H statistic	14.33	8.45
p-value	<0.001	0.013
Dunn Test (with Bonferroni correction)		
PG&E vs SCE	<0.001	0.01
PG&E vs SDG&E	0.07	0.64
SCE vs SDG&E	1.00	1.00

To assess P2P-EVSE viability across different foreseen and unforeseen electricity rates, we conducted a three-part (low/average/high) sensitivity analysis comparing potential renter discounts and host markups against public and residential electricity rates. This analysis focused on overall patterns and distributions rather than individual renter-host pairings, providing insights into potential P2P-EVSE adoption across regions and rate structures.

We obtained residential electricity rates from PG&E, SCE, and SDG&E websites. These utilities offer various rate plans, including tiered rates, time-of-use (TOU) rates, electric home rates, and electric vehicle (EV) rates. P2P-EVSE shows the highest viability under EV rate plans, which feature lower off-peak rates during night, morning, and before-evening peak hours. Unlike standard TOU plans, EV rate plans lack baseline allocation restrictions that would increase prices for above-baseline electricity consumption, allowing hosts to maintain consistent per-kilowatt-hour (kWh) costs regardless of total consumption.

Our analysis focused on PG&E's EV-B plan for Northern California and averaged rates from SCE's TOU-D-PRIME and SDG&E's TOU-ELEC plans for Southern California. The analysis considered base electricity fees per kWh, excluding additional charges such as taxes, flat fees, or other surcharges. We also ignored any discounts that qualified low-income households may receive[6]. While this approach underestimates true host costs, it provides the most reliable analysis given electricity consumption uncertainties.

For public charging rates, we analyzed fast-charging EV station provider data, estimating an average rate of $0.50 per kWh[7], excluding additional fees such as taxes, memberships, parking fees, or idle charges. Given the complexity of charging companies' pricing algorithms, we established low, average, and high-rate scenarios for both public and residential charging, applying 20% adjustments from our average estimates.

To evaluate potentially successful matches between renters and hosts, we analyzed survey responses regarding discount and markup expectations. Renters specified minimum required discounts compared to public charging rates, while hosts indicated minimum markup requirements over residential electricity rates. We assessed nine scenarios combining three levels each of public and residential electricity rates (Low, Average, High).

[6] Recipients of these bill discounts receive 18% to 30% off their monthly electric bills and could earn more money from P2P-EVSE than other hosts. However, most utilities disclose that households receiving these discount programs are at risk of losing this benefit it their energy use is excessive. Thus, it is recommended that utilities decouple building energy consumption and EV consumption when offering these discounted rates.

[7] This value is in line with Kandhra et al.'s (2024) public charging rates taken from crowd-sourced data and pricing data from an EVSP.

Our analysis reveals significant regional differences in the potential for P2P-EVSE adoption:

1. Southern California (SCE & SDG&E):

    - High potential for matches across all scenarios, with 100% match probability in many cases.
    - Even in the least favorable scenario (low-cost public charging and high-cost residential charging), there remains a 27.41% chance of successful matches.
    - This suggests a robust potential for P2P-EVSE adoption in Southern California.

2. Northern California (PG&E):

    - Lower overall match probabilities compared to Southern California.
    - Highest match probability (100%) only occurs in the most favorable scenario (high-cost public charging and low-cost residential charging).
    - Many scenarios show very low or zero match probabilities, particularly when public rates are low or residential rates are high.

Calculating Renters' Maximum Acceptable Price:

For each renter, we calculated their maximum acceptable price per kilowatt-hour (kWh) using the formula:

$$\text{Renters' Maximum Price} = \text{Public Rate} \times \left(1 - \text{Renters' Required Discount } (\%)\right)$$

This calculation determines the highest price a renter is willing to pay, given their desired discount off the public rate.

Calculating Hosts' Minimum Acceptable Price:

For each host, we determined their minimum acceptable price per kWh with the formula:

$$\text{Hosts' Minimum Price} = \text{Residential Rate} \times \left(1 + \text{Hosts' Required Markup } (\%)\right)$$

This yields the lowest price a host is willing to accept, factoring in their desired profit margin over their residential electricity cost.

Establishing Matching Criteria:

A successful match between a renter and a host is possible when:

$$\text{Hosts' Minimum Price} \leq \text{Renters' Maximum Price}$$

This condition ensures that the host's required price does not exceed what the renter is willing to pay.

Identifying Acceptable Renters and Hosts:

- Acceptable Renters: We calculated the proportion of renters whose maximum acceptable price meets or exceeds the hosts' minimum acceptable price in each scenario.
- Acceptable Hosts: We determined the proportion of hosts whose minimum acceptable price is at or below the renters' maximum acceptable price in each scenario.
- Calculating the Probability of Successful Matches:

Assuming the decisions of renters and hosts are independent, the probability of a successful match in each scenario is given by:

$$\text{Probability of Match} = \left(\frac{\text{Number of Acceptable Renters}}{\text{Total Number of Renters}}\right) \times \left(\frac{\text{Number of Acceptable Hosts}}{\text{Total Number of Hosts}}\right) \times 100\%$$

This formula calculates the joint probability that a randomly selected renter and a randomly selected host are mutually acceptable in terms of price.

The more favorable conditions for P2P-EVSE adoption in Southern California can be attributed to lower residential electricity rates, especially during off-peak hours, and relatively higher public charging rates. This larger differential between public and residential rates enhances economic incentives for both renters and hosts, increasing the likelihood of mutually acceptable pricing and successful matches on P2P-EVSE platforms. In contrast, Northern California presents more challenges for P2P-EVSE adoption due to a smaller cost disparity in rates. Results are presented in Tables 8 and 9 for both regions.

Even with EV-specific rate plans, the difference between residential and public charging rates in Northern California may remain smaller compared to Southern California. While this suggests P2P-EVSE may not be as appealing for routine charging needs in this region, it could still play a valuable role in specific scenarios. In areas with inadequate public charging infrastructure or limited access to shared private chargers, P2P-EVSE can provide essential charging options for EV owners.

Additionally, during emergency evacuations, such as natural disasters when charging demand surges and queues at public stations lengthen, P2P-EVSE can offer alternative charging solutions. By reducing congestion at public charging stations, it can support more efficient evacuation efforts and enhance overall emergency response capabilities.

To improve P2P-EVSE viability in regions like Northern California, several strategies could be considered. First, residential P2P-EVSE charging costs during off-peak hours could be offered at a lower rate if EVSE can conform to or receive a waiver to measurement standards[8] (California Department of Food and Agriculture Division of Measurement Standards, 2020). Second, policymakers could consider incentives that make P2P-EVSE more attractive for both hosts and renters by introducing subsidies, tax credits, or rebates. By addressing regional challenges and tailoring strategies accordingly, it may be possible to enhance the adoption and effectiveness of P2P-EVSE platforms across different parts of California. It is important to note that this analysis is based on current rate structures and user expectations. As the EV market evolves and users become more familiar with P2P-EVSE concepts, these dynamics could change.

Table 4.5: Southern California EV Respondents' Potential P2P-EVSE Price Match

	Public Low ($0.40)	**Public Avg ($0.50)**	**Public High ($0.60)**
Residential Low ($0.19)	183 renters, 183 hosts (100.00%)	183 renters, 183 hosts (100.00%)	183 renters, 183 hosts (100.00%)
Residential Avg ($0.23)	145 renters, 152 hosts (65.81%)	183 renters, 183 hosts (100.00%)	183 renters, 183 hosts (100.00%)
Residential High ($0.28)	85 renters, 108 hosts (27.41%)	145 renters, 156 hosts (67.54%)	183 renters, 183 hosts (100.00%)

Note: The Southern California region encompasses SCE & SDG&E utilities (n = 183).

Table 4.6: Northern California EV Respondents' Potential P2P-EVSE Price Match

	Public Low ($0.40)	**Public Avg ($0.50)**	**Public High ($0.60)**
Residential Low ($0.30)	81 renters, 68 hosts (38.25%)	108 renters, 110 hosts (82.50%)	120 renters, 120 hosts (100.00%)
Residential Avg ($0.37)	7 renters, 3 hosts (0.15%)	82 renters, 69 hosts (32.29%)	100 renters, 109 hosts (75.69%)

[8] This is important because it avoids requiring a second meter (see PG&E's EV-B plan).

Residential High ($0.44)	0 renters, 0 hosts (0%)	21 renters, 10 hosts (1.46%)	82 renters, 69 hosts (39.29%)

Note: The Southern California region encompasses PG&E utilities (n = 120).

Chapter 5 Discussion

5.1 Barriers and Opportunities in Scaling P2P-EVSE Platforms

P2P-EVSE platforms represent an innovative solution in the evolving landscape of EV charging infrastructure. Our analysis reveals both promising potential and significant challenges for this emerging market. The supply-side potential is substantial: with 39% of surveyed California EV drivers having Level 2 EVSE at home and 38.6% of these owners expressing willingness to become hosts, up to 170,000 private chargers could potentially enter P2P-EVSE platforms across California (California Energy Commission, 2024b). This figure exceeds the current number of public and shared private chargers statewide as of August 2024 (California Energy Commission, 2024a), suggesting significant potential for expanding charging access through P2P networks.

However, several critical factors may limit market development. The first barrier that emerges is user walking preferences. With 12.8% of potential renters willing to walk only two minutes and 36.2% limiting their walk to five minutes one-way, P2P-EVSE may not effectively address unserved home charging needs. In order to remedy home charging barriers, which is estimated to affect at least 30% of households (Alexander, 2022), other near-home charging alternatives must be considered that could compete with P2P-EVSE platforms, including curbside charging, neighborhood charging stations, and subsidizing charging at multifamily properties.

The second barrier is price matching between hosts and renters. Regional variations in electricity rates significantly impact the viability of P2P-EVSE adoption. Our data indicates that EV drivers in Southern California (SCE and SDG&E territories) are more likely to find acceptable price matches under average market conditions. In contrast, PG&E ratepayers in Northern California face more challenging economics, with match probability falling below 33% under current market conditions. The reason for this divide is that there is a wider price gap between residential and public charging rates in Southern California than in the North.

Beyond economic and walking distance barriers, several institutional and technical challenges could impede P2P-EVSE adoption. Homeowners associations (HOAs) may restrict or prohibit commercial activities in residential areas, potentially limiting participation among homeowners in planned communities. Some HOAs might classify P2P-EVSE as a commercial enterprise, requiring special permits or outright prohibiting the practice. Similarly, local zoning regulations and parking ordinances could restrict curbside charging access, particularly in dense urban areas where street parking is already limited.

Technical compatibility presents another significant barrier. Our survey revealed that 43.6% of respondents with home charging were Tesla owners, who typically have proprietary charging equipment. While Tesla owners can use and own adapters to charge at Combined Charging System (CCS) stations, many non-Tesla EV owners generally do not use Tesla charging equipment. This asymmetry in charging compatibility could limit the effective matching of hosts and renters, particularly if most potential hosts are Tesla owners while renters predominantly drive other EV brands. The cost and availability of adapters, along with potential warranty and liability concerns related to their use, could further complicate P2P-EVSE adoption.

These implementation barriers suggest that successful P2P-EVSE platforms may need to work closely with local authorities and HOAs to establish clear guidelines for residential charging sharing, while also developing strategies to address charging compatibility issues, possibly through adapter provision programs or clear communication about charging equipment compatibility during the booking process.

5.2 Limitations

This study provides valuable insights into the perceptions and potential adoption of P2P-EVSE platforms in California; however, several limitations should be acknowledged. Our research relied on a sample of 367 California residents who own or lease plug-in EVs, recruited through Prolific. While this approach allowed for targeted sampling of EV owners, it may not fully represent the broader population of California EV drivers. The study relies on self-reported data, which can be subject to social desirability bias or recollection errors and may not reflect actual behaviors or future actions. For respondents without home charging or Level 2 chargers, we asked them to assume they had Level 2 chargers when considering hosting scenarios. This hypothetical framing may not fully capture the real-world decision-making process of potential P2P-EVSE hosts. Additionally, the survey's length (approximately 17 minutes) could have led to respondent fatigue, potentially affecting the quality of responses.

Our analysis, comparing BLR models with and without attitudinal factors revealed important considerations. Changes in the significance levels for some variables between the two models, such as travel modes like e-scooter or biking in the renter model, suggest that attitudinal factors may be capturing some of the effects previously attributed to travel behavior. This indicates a complex interplay between behavioral and attitudinal factors that warrants further investigation. The inclusion of PCA for attitudinal variables not captured by factor analysis provided additional insights but also introduced complexity in interpreting the results.

The regional analysis of renter discounts and host markups, while informative, was limited to the service areas of three major IOUs. This approach, while covering a significant portion of California, may not fully capture the nuances of electricity pricing and EV charging behavior in areas served by smaller utilities or community choice aggregators. The sensitivity analysis comparing potential renter discounts and host markups against public and residential electricity rates provides valuable insights but relies on several assumptions. The use of average rates and the exclusion of additional charges (such as taxes and fees) may not fully reflect the complex pricing structures in real-world scenarios.

California has a unique regulatory environment, EV adoption rate, and spread of public chargers compared to other states, and findings may not be applicable to regions with different EV policies, infrastructure, or cultural attitudes towards sharing. The P2P-EVSE market is rapidly evolving, especially in Europe, where these platforms may be more readily accepted due to factors such as space constraints, higher population density, and a more developed culture of shared mobility. Our findings represent a snapshot of perceptions in California in April-June 2024 and may not reflect future attitudes as the technology and market mature.

Despite these limitations, these findings can serve as a foundation for future research and inform the development of P2P-EVSE platforms and related policies. Future studies could benefit from more diverse sampling methods and the inclusion of actual usage data from P2P-EVSE platforms as they become more widespread. Additionally, cross-cultural comparisons, particularly with European markets, and investigation of specific regional factors affecting adoption would provide valuable insights for platform development, policy initiatives, and infrastructure planning.

5.3 Conclusions

Our study provides the first comprehensive analysis of P2P-EVSE adoption potential in California, revealing key insights into both host and renter perspectives. The findings highlight a complex interplay of benefits, risks, and regional factors that influence platform viability. Several key conclusions emerge from our analysis.

Host and renter attitudes demonstrate clear benefit-risk trade-offs. For hosts, potential charger damage is the primary concern, followed by liability issues, while maintaining control over the hosting process (including booking approval and availability settings) is highly valued. Renters primarily worry about liability-related issues, particularly regarding vehicle damage from faulty equipment. Both groups identify monetary advantages as the primary benefit, with renters also valuing convenience.

Despite potential benefits, only about a third of surveyed EV drivers expressed willingness to participate in P2P-EVSE platforms—28% as hosts and 31% as renters. Results from the final binary logistic regression models indicate that while single-family detached housing residents are less likely to become hosts, home ownership tempers this effect.

Non-White and non-Asian Americans have a higher propensity to become renters, but this effect is moderated when controlling for Tesla vehicles. Further, PHEV owners are 2.48 times more likely to become renters compared to BEV owners.

However, willingness to participate alone doesn't guarantee viable matches between hosts and renters. Price disparities between home and public charging can impact economic viability. Southern California (SCE and SDG&E territories) shows robust potential for successful matches across various pricing scenarios, maintaining at least 27.41% match probability even under unfavorable conditions. In contrast, Northern California (PG&E territory) demonstrates limited matching potential, with probabilities below 33% under current market conditions, highlighting the crucial role of regional electricity rate structures in P2P-EVSE viability.

These findings contribute to both academic literature and practical implementation. First, they provide a comprehensive analysis of host-renter perspectives in a major EV market. Second, they identify key socioeconomic and attitudinal factors influencing P2P-EVSE adoption. Third, they reveal regional variations in economic viability and analyze critical factors such as walking distance preferences. These insights can help P2P-EVSE companies refine their offerings and attract customers. They also suggest to policymakers that P2P-EVSE is a large and untapped resource that could help address near-home charging barriers, a known obstacle to EV adoption.

Future research should explore several key directions to build upon these findings. While our study captured stated preferences for P2P-EVSE, a discrete choice experiment could better quantify how acceptance varies with key attributes such as charging duration, walking distance, and cost. Such an experiment could present users with realistic trade-offs between P2P-EVSE and alternative charging locations. This approach, combined with more advanced models could jointly estimate charging choices alongside attitudinal constructs. Additionally, longitudinal studies could track how attitudes towards P2P-EVSE evolve as the market matures, and future studies could survey other regions. As these platforms become operational, studies of actual usage patterns and user experiences will be crucial for validating and refining our findings.

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