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Behavioral Segmentation and Causal Evidence on Public Charging Preferences of Electric Vehicle Users

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ABSTRACT

In this study, we propose an integrated analytical framework combining factor analysis, latent profile analysis, and causal inference using survey data from over 360 Battery Electric Vehicle (BEV) owners across 44 survey items related to infrastructure features, time and cost constraints, situational factors, and vehicle characteristics. We first extract eight latent dimensions that structure charging station evaluations, capturing not only technical and economic considerations but also trust in provider reliability, situational convenience, and EV-specific constraints. Building on these factors, we uncover two distinct user profiles: Efficiency-Oriented Users, prioritizing predictable access, minimal detours, and low waiting times, and Information-Responsive Users, who prioritize availability of co-located amenities, compatibility with daily routines, and EV-specific requirements, highlighting substantial heterogeneity in how drivers prioritize infrastructure features. Using inverse propensity weighting, we estimate the causal effects of private charger access, public charging frequency, opportunistic charging behavior, and EV usage purpose on profile membership. Our results reveal that access to private chargers and frequent public charging are key drivers of more selective, context-sensitive station evaluations associated with the Information-Responsive profile. We also find that trip purpose strongly conditions station priorities, with business-related users emphasizing reliability and situational compatibility. These findings underscore that expanding charger availability without addressing informational, contextual, and experiential needs will fall short of building equitable and sustainable EV infrastructure. Planning strategies must recognize user heterogeneity, anticipate differentiated demands, and integrate charging ecosystems into the fabric of routine urban mobility.

1. Introduction

Over the last decade, electric vehicle (EV) adoption has surged, with the number of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) in the U.S. increasing from 0.2 million in 2013 to 4.8 million in 2023 [1]. Additionally, the share of new EV sales rose sharply, from 7% in 2022 to 10% in 2023 [1]. This upward trajectory is expected to continue, with projections forecasting up to 12.8 million EV sales in the U.S. by 2035 [1]. Several factors underpin this rapid growth, including advancements in battery technologies [2], the introduction of stronger policy incentives [3], and growing consumer awareness of EV benefits [4]. As adoption accelerates, the large-scale expansion of public charging infrastructure emerges as an essential enabler, particularly for users without reliable access to private charging options, facilitating ease of travel within and between urban areas. However, such infrastructure build-out raises critical questions about its long-term sustainability, many of which are deeply intertwined with patterns of EV user behavior. In particular, many regions exhibit highly uneven charging station usage, where a small number of stations account for a disproportionate share of total visits, while others remain largely underutilized [5, 6]. Explanations for this inequality might point to deficiencies in service reliability [7] or access barriers at certain sites [8] but such arguments risk overlooking a more fundamental gap: the lack of a clear and structured understanding of how and why EV users evaluate and choose between available charging stations.

This knowledge gap is rooted in both the limited scope and methodological shortcomings of existing research. Most studies emphasize a narrow set of observable station attributes such as proximity [9], cost [10], or charging

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speed [11], while neglecting experiential and contextual factors that users often weigh during real-world decision-making. Attributes like prior satisfaction [12], user reviews [13], trust in charging providers [14], or situational constraints [9] (e.g., availability of nearby amenities or compatibility with travel routines) are rarely measured or modeled with sufficient granularity, even though they play critical roles in shaping perceived reliability, comfort, and integration of charging into daily life. Accounting for these dimensions is essential, as they introduce new behavioral contexts where users may prioritize convenience, daily routine fit, or trusted recommendations over purely technical specifications. Moreover, much of the literature assumes user preferences are homogeneous, treating EV users as a uniform group despite growing evidence of meaningful heterogeneity in usage patterns and charging priorities [12]. Even when segmentation is attempted, it often relies on surface-level demographic or vehicle ownership characteristics without systematically connecting preference structures to underlying behavioral routines [15]. Moreover, studies often interpret survey findings through descriptive correlations, conflating structural factors such as access to private charging infrastructure or neighborhood station density with self-selection based on user choices or habits. For example, users who frequently prioritize stations with co-located amenities or trusted network providers may not do so because of inherently different preferences, but rather because they have greater flexibility enabled by private home charging access or lower time constraints during travel. Therefore, without accounting for these structural differences, observational patterns risk being misinterpreted as intrinsic user preferences, rather than outcomes shaped by infrastructural and behavioral conditions. Failing to disentangle these dynamics limits the ability to identify causal factors of behavior, obscures the conditions under which preferences emerge, and hinders the development of targeted infrastructure strategies tailored to diverse user needs.

To address these limitations, this study draws on a detailed survey of BEV owners to analyze charging station selection preferences. We first reduce the dimensionality of 44 survey items related to infrastructure features, time and cost constraints, situational factors, and vehicle characteristics, identifying a set of latent behavioral dimensions that structure how users evaluate public charging stations. These latent factors provide an interpretable basis for uncovering the underlying factors of station selection decisions. Building on these factors, we probabilistically segment users into distinct profiles based on the similarity of their prioritization strategies, capturing meaningful differences in how users balance technical, situational, and experiential considerations when selecting charging stations. Furthermore, to understand the factors behind these profiles, we apply a causal framework that approximates a quasi-randomized experiment by reweighting observations based on observed characteristics. This approach enables us to estimate the effect of key behavioral and infrastructural factors such as private charger access, public charging frequency, opportunistic charging behavior, and EV usage purpose on profile membership. Through this integrated procedure, we specifically explore three main research questions:

RQ1 Building on a user-centric framework for analyzing charging infrastructure preferences [15], we ask what are the underlying latent dimensions that structure how EV users evaluate public charging stations, and how can these be empirically identified from a broad set of survey items?

RQ2 Can EV users be grouped into distinct preference profiles based on how they prioritize different charging station attributes, and what characterizes each group?

RQ3 To what extent do specific behavioral and infrastructural factors, such as charging frequency, driving purpose, or private charger access, causally influence the likelihood of belonging to each preference profile?

By answering these questions, we seek to uncover the factors behind divergent charging station evaluation strategies among EV users, and provide actionable insights for infrastructure planners, policymakers, and behavioral researchers. In doing so, we aim to support more targeted, effective, and equitable deployment of public charging infrastructure. The rest of the paper is organized as follows. Section 2 reviews the literature on charging station selection and highlights methodological gaps. Section 3 introduces the survey data and summarizes the variables used. Section 4 presents the factor extraction, profile segmentation, and causal inference framework. Section 5 reports the main findings, and Section 6 interprets the results in light of planning and policy implications and concludes with a discussion of limitations and directions for future work.

2. Background

The adoption of EVs remains an essential component of state-wide energy resilience goals. Several states, including California and New York, have set ambitious goals to ensure that 100% of new passenger vehicles sold are zero-emission vehicles (ZEVs) by 2035, with Oregon targeting a 90% adoption rate [16]. At the same time, the price gap between gasoline vehicles and EVs is expected to narrow, removing one of the main barriers to EV adoption [17, 18]. Nevertheless, sufficient access to charging infrastructure remains a significant hurdle that must be overcome to drive the uptake of EVs [19, 20]. Therefore, the sustainable development of charging infrastructure, in line with the rate of EV adoption, is crucial for achieving environmental and energy goals. This requires a thorough understanding of the factors that influence users' choices and preferences regarding charging stations. Without this insight, we risk creating a situation where a small number of stations serve the majority of user demand, leading to underutilization of many stations and inequitable access across different communities [21, 22].

To gain a clear understanding of the existing potentials and challenges within the expansion of charging infrastructure and EV adoption, conducting surveys remains an invaluable tool for capturing direct responses from diverse user groups regarding their preferences. Studies have indicated that different EV users may have distinct preferences about charging infrastructure, assigning different levels of importance to factors such as range anxiety, accessibility, and the capacity of charging stations [23, 24, 25, 26]. Additionally, an analysis aiming to identify users' perceptions and preferences should include individual user attitudes and their experiences with the actual infrastructure. In this regard, studies have found factors related to charging infrastructure, such as location [27], number and type of chargers [14, 28], energy source [29], and charging time [30] to be significant in charging station selection. Additionally, certain factors related to user perceptions, such as range anxiety and battery range [31], and situational characteristics of charging, such as time of day [32], home charging availability [33], and detour time [34], have also been found influential in users' selection of charging stations.

Despite the exploration of various factors to understand users' perceptions of charging stations, certain elements that might influence the decision-making process are often overlooked. For instance, this includes factors related to the social influence of selecting a charging station, especially for potential adopters or those with less experience using charging stations. In such cases, users might rely on recommendations from their social circle (e.g., friends and family), reviews of the stations by other users, and their own experiences if applicable [33]. Furthermore, even when such attributes are included, their definitions often lack alignment with real-world user behavior. For example, the measures of accessibility often only focus on distance to the nearest charger, without accounting for the opportunity to engage in nearby activities, such as dining or shopping, while charging their vehicle [35]. This is also important to include since, due to the longer charging times, EV users often prefer to visit other activity locations during the charging process [11, 36]. This limited view restricts our ability to capture the full spectrum of preferences and behaviors that govern station selection. As a result, infrastructure planning efforts may mischaracterize the factors that matter most to users, potentially leading to underutilized assets or unmet user needs.

Furthermore, a critical but often overlooked dimension of charging station planning is the recognition that EV users are not a homogeneous group [12]. Individuals vary widely in how they prioritize infrastructure features, the constraints they face, and the contexts in which charging decisions are made. Some may focus exclusively on minimizing cost or travel time, while others may prioritize safety, convenience, or the presence of nearby services. These differences are not random and instead they reflect variations in lifestyles, vehicle usage patterns, access to private infrastructure, and broader social and economic positioning [37]. Without explicitly accounting for this heterogeneity, policies aimed at improving infrastructure access or encouraging behavioral shifts risk targeting an average user that does not meaningfully represent any specific segment. Segmenting users based on their charging preferences allows for more targeted and effective interventions. For instance, financial incentives or information campaigns may resonate differently with users who charge primarily at home versus those who rely on public infrastructure. Similarly, infrastructure improvements such as adding amenities or ensuring price transparency may disproportionately benefit certain user segments, depending on their stated priorities. Recognizing these segments can also enhance demand forecasting and equity assessments, as it allows planners to evaluate whether infrastructure investments meet the needs of both high-frequency public chargers and more infrequent, routine-based users.

While surveys have played a central role in identifying the factors that influence charging station preferences, most analyses remain descriptive in nature. In this regard, traditional methods of analyzing surveys on charging infrastructure perceptions and preferences often rely on summary statistics or visual presentations to illustrate differences between survey variables. More comprehensive approaches employ techniques such as choice experiments [38], sensitivity analysis [39], or employ principal component analysis [40]. Nevertheless, while such studies report associations between user characteristics and stated preferences, they stop short of disentangling whether these relationships reflect causal mechanisms or merely reflect correlations driven by unobserved factors. As a result, we lack clarity on whether key attributes, such as access to private chargers, frequency of public charging, or usage purposes, actively shape users' decision-making processes, or whether they simply co-occur with certain stated preferences. This methodological gap limits the actionable insights that can be derived from surveys, particularly when designing interventions or infrastructure that aim to influence behavior rather than just observe it. Incorporating a causal inference framework enables a more rigorous examination of how behavioral, infrastructural, and contextual factors affect the likelihood of adopting distinct charging preference profiles. This is especially important when assessing the impact of factors such as home charger availability, opportunistic charging behavior (e.g., plugging in whenever a charger is available, regardless of battery state), or business-related EV use (e.g., frequent charging during work trips). These factors are potentially endogenous to socioeconomic status or mobility needs, but are rarely analyzed as causal drivers in the literature. By estimating the direction and magnitude of these effects, a causal framework can provide a stronger empirical basis for identifying leverage points in infrastructure planning and for designing user-specific interventions that go beyond one-size-fits-all strategies.

Based on our review of the literature, it is evident that understanding users' perceptions and preferences regarding charging infrastructure is essential for developing a public charging system that is both sustainable and responsive to real-world usage patterns. This exploration must move beyond narrow sets of attributes to incorporate a wider range of influencing factors including technical features, contextual constraints, and experiential needs, while also accounting for heterogeneity across user segments and identifying the causal mechanisms that shape preference formation. To address these limitations, we design a targeted survey of EV users that captures both stated preferences and contextual factors across 44 attributes related to infrastructure, cost, time, situational routines, and vehicle characteristics. This comprehensive coverage allows us to identify the latent dimensions that structure station evaluation. We then apply a probabilistic segmentation approach to uncover distinct user profiles based on these dimensions, enabling a structured analysis of preference heterogeneity. Finally, we adopt a causal inference framework to estimate the effect of key behavioral and infrastructural exposures such as private charging access, charging frequency, and driving purpose on profile membership. Together, these components provide a methodologically integrated approach to understanding how EV users make charging decisions and what levers can inform more effective and equitable infrastructure strategies.

3. Data

3.1. Survey Design and Procedure

This study draws on a subset of data from a larger online survey designed to capture attitudes, preferences, and behaviors related to EV adoption and usage. Our analysis focuses specifically on the portion of the survey related to public charging station selection and includes only respondents who identified as current EV users. The full online survey comprises 89 questions in two main sections: participant background and user preferences regarding their perceptions and interactions with the charging infrastructure. More specifically, the first section of the survey collects demographic information, including state of residence, age, gender, race, education, employment status, income, and vehicle ownership status and type. Only U.S. residents above the age of 18 were eligible to complete the survey. The second part of the survey includes questions organized into two thematic areas. The first theme explores participants' interactions with and preferences regarding EVs, such as their priorities when considering a potential EV purchase (e.g., *"If you were to buy an electric car tomorrow, what would be the most important features for you in your choice of an electric car?"*). The second theme focuses on public charging behavior, including preferences for station attributes and individual charging patterns (e.g., *"Which of the following characteristics or features would be important to you when choosing a charging station?"*). The third theme addresses participants' broader environmental attitudes, capturing their perspectives on the human–nature relationship and ecological values (e.g., *"Humans have the right to modify the natural environment to suit their needs."*) [41]. Additionally, participants were given the opportunity to provide open-ended comments about the survey. Finally, participants were recruited via Prolific Academic (ProA), a crowdsourcing platform for recruiting online participants for research [42, 43].

3.2. Descriptive Statistics

3.2.1. Participants' Background

Our analysis focuses on a subpopulation of 365 respondents who identified as current EV owners, drawn from a larger survey sample of 997 valid responses, as detailed in Reimer et al. [15]. EV respondents had a median age of 37 years, with ages ranging from 19 to 71. The sample includes 60.6% male and 39.2% female participants. In terms of racial and ethnic composition, 55.1% identified as White, 24.1% as Black, 12.3% as Asian, and the remaining 8.5% as Hispanic or another group. Educational attainment is relatively high with 45.8% of respondents holding a Bachelor's degree, 35.1% a graduate degree, 9.6% an associate or junior college degree, and 9.6% a high school diploma or less. Most participants are employed full-time (80.0%), while 12.3% work part-time and the remainder are retired or unemployed. In terms of annual household income, 22.3% report earning over $150,000, 15.9% between $110,000 and $150,000, and 28.0% between $75,000 and $110,000. A smaller share (14.6%) earn between $25,000 and $60,000, while 8.0% report incomes below $25,000. Regarding political affiliation, 56.1% identified as liberal, 34.0% as conservative, and 9.9% as independent.

3.2.2. Participants' Perceptions and Preferences

The survey included a comprehensive set of questions designed to capture how participants perceive, evaluate, and engage with EV charging infrastructure. To support nuanced behavioral modeling, questions were customized by ownership status. While all participants answered questions related to EV adoption and environmental attitudes, only current EV users were asked about their specific charging routines and public station selection preferences. Nevertheless, here we focus exclusively on current EV users ($N = 365$) to enable a deeper analysis of charging behavior within the context of actual preferences rather than hypothetical intentions. All perception and preference items were presented using a five-point Likert scale ranging from 1 ("not at all important") to 5 ("very important"), allowing participants to express the relative weight they assign to various infrastructure, behavioral, and situational factors. Among the 44 items analyzed, key themes included attributes of charging providers (e.g., energy source, network affiliation), availability of amenities near charging locations (e.g., dining and retail), physical accessibility and reliability of stations (e.g., socket availability, speed), and time- or cost-related constraints. These items are grouped into several broader categories, summarized in Table 1, which presents the distribution of responses across all five Likert levels.

Participants were also asked about their behavioral charging routines, including frequency of charging (e.g., "How often do you charge your electric vehicle?"), battery management strategies (e.g., "Do you typically charge only when your battery is nearly empty?"), and whether they engage in small, opportunistic charging when the opportunity arises. These behavioral treatments complement the stated preferences by capturing real-world patterns of station interaction. Furthermore, to contextualize preferences within broader social and mobility settings, the survey included additional questions on usage purpose (whether the EV is primarily used for business, commuting, or social trips), and a social treatment measure asking respondents how many people in their social network (friends and family) regularly drive EVs.

Table 1: Survey items on charging station preferences among EV users ($N = 365$)

Category	Abbr.	Description	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
Provider	ATT1	Energy source of power station: The type of energy source that is used to generate electricity at the charging station, such as solar, wind, or grid electricity.	13.7	16.7	26.0	23.8	19.7
	ATT2	Charging network provider: The company or network providing the charging station services.	8.5	13.4	25.8	29.3	23.0
	ATT3	Vehicle-to-grid (V2G) capabilities: Whether your electric vehicle can contribute power back to the grid.	23.8	18.4	27.1	18.9	11.8
	ATT4	Battery swapping/switching: Whether the charging station offers battery swapping or switching services.	29.6	14.5	23.3	16.7	15.9
Amenities	ATT5	Amenities: Access to a restaurant or shopping mall next to the charging station.	2.7	11.5	24.4	33.4	27.9
	ATT6	Opportunities for other activities during charging: Whether you can engage in other activities, such as shopping or working, while your vehicle is charging.	2.2	7.7	23.0	37.8	29.3

Category	Abbr.	Description	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
Accessibility	ATT7	Accessibility of charging station: The overall ease of reaching the charging station.	0.3	1.9	10.1	30.7	57.0
	ATT8	Location area of charging station: The geographical area where the charging station is located, like residential, work, or commercial locations.	1.1	3.3	17.0	32.3	46.3
	ATT9	Available sockets/piles (#): The number of available charging outlets or piles at the charging station.	0.5	2.7	11.5	35.9	49.3
Cost	ATT10	Charging cost: The amount of money you have to pay for charging your electric vehicle.	0.3	3.0	14.8	24.7	57.3
	ATT11	Price savings: The amount of money you save by using a specific charging station.	1.4	6.0	19.2	29.9	43.6
	ATT12	Parking cost: The cost of parking your electric vehicle at the charging station.	2.7	5.5	16.4	32.6	42.7
	ATT13	Perfect information (about price): The degree to which you have access to complete and accurate information about charging station prices.	0.5	3.0	18.6	34.5	43.3
Experience	ATT14	Previous satisfaction: Whether or not you have visited a charging station before and were satisfied with the experience using it.	1.4	5.5	17.8	38.9	36.4
	ATT15	Recommendations by friends and family: Recommendations by friends and family when exploring a new charging station.	10.1	15.1	25.8	28.8	20.3
	ATT16	Reviews: Previous user reviews when trying out a new charging station.	2.5	8.5	22.2	36.2	30.7
Time	ATT17	Valet-charging: Whether the charging station offers valet services for charging your electric vehicle.	37.5	14.8	18.4	16.7	12.6
	ATT18	Charging duration: The time it takes your electric vehicle to charge completely.	0.0	0.8	10.4	36.7	52.1
	ATT19	Charging speed: The category of the charging station, such as level 1, level 2, or DC fast, indicating the charging speed it offers.	0.0	3.0	9.9	26.8	60.3
	ATT20	Detour distance/travel time: The additional distance or time you have to travel out of your way to reach a charging station.	1.4	3.6	19.7	40.3	35.1
	ATT21	Travel Time: The time it takes to reach the charging station from your current location.	1.4	3.3	20.0	39.7	35.6
	ATT22	Waiting time (min): The amount of time you have to wait in line before you can start charging your electric vehicle.	0.5	4.9	12.3	27.9	54.2
	ATT23	Idle time at charging station: The amount of time you spend waiting at a charging station during the charging process.	2.5	5.5	21.4	34.5	36.2
EV Characteristics	EXO1	I typically charge when I do not have enough battery power for the next trips I plan.	1.9	1.9	14.2	30.1	51.8
	EXO2	I typically charge when the state of charge falls to a certain level.	1.4	5.2	21.4	32.6	39.5
	EXO3	I typically charge when the battery is empty/discharged.	1.1	3.0	12.1	30.7	53.2
	EXO4	I typically charge when I am below a specific buffer range that I always want to have in the battery.	6.0	9.9	23.8	27.9	32.3
Driver Perception	EXO5	Range anxiety: The level of concern or worry you experience about running out of battery power before reaching your destination.	1.9	9.3	18.4	31.8	38.6
	EXO6	Driver risk attitudes: Your personal attitude towards risk and safety while driving an electric vehicle.	5.8	12.1	26.8	29.3	26.0
	EXO7	Environmental consciousness: Your level of concern and commitment to environmental issues and sustainability.	6.6	9.9	26.6	30.4	26.6
	EXO8	Awareness of charging infrastructure: Your level of knowledge and awareness of available charging stations.	1.4	6.6	26.0	36.4	29.6
Charging Opportunity	EXO9	Home charging availability (garage): Whether you have the option to charge your electric vehicle at home in your garage.	0.8	3.3	14.5	29.9	51.5
	EXO10	Number of charging stations: The number of charging stations that are within a driving range of your vehicle.	1.4	4.1	16.7	37.5	40.3
	EXO11	Workplace charging availability: Whether your workplace provides charging facilities for electric vehicles.	7.7	11.2	22.5	30.1	28.5
	EXO12	Distance between charging stations: The distance between the closest charging station and the next one on your route.	0.5	5.2	17.0	34.2	43.0

Category	Abbr.	Description	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
	EXO13	Availability on your way: Availability of charging stations in your daily activities routine (e.g., going to work, shopping, etc.).	1.9	4.4	15.9	34.8	43.0
	EXO14	Number of household vehicles: The total number of vehicles owned by your household.	17.0	18.9	25.8	24.1	14.2
Situational Time	EXO15	Frequency of charging events: Number of times you need to charge during a week/month.	2.7	7.4	23.6	38.1	28.2
	EXO16	Day of the week: Your preference to charge your vehicle during weekdays or weekends.	19.7	17.5	22.2	27.1	13.4
	EXO17	Daytime/night: Your preference for charging after working hours or before working hours.	6.6	11.8	26.8	29.0	25.8
	EXO18	Driving schedule: The typical schedule or routine for driving your electric vehicle.	3.3	8.2	26.8	35.6	26.0
	EXO19	Dwelling time at destination: The duration of your stay at your destination, affecting the opportunity to charge.	3.0	6.6	25.8	35.3	29.3
	EXO20	Number of daily trips: The average number of trips you take in your electric vehicle each day.	5.2	12.9	27.9	32.1	21.9
	EXO21	Season: Your preference or pattern for charging during different seasons of the year.	15.6	18.4	27.9	27.1	11.0

4. Methodology

To examine the behavioral dynamics shaping charging station selection, we develop a multi-stage methodology grounded in survey responses introduced in Section 3. As illustrated in Figure 1, our approach first applies factor analysis to distill key dimensions of charging preferences from a high-dimensional set of attitudinal questions. This dimensionality reduction step reveals latent constructs that structure how individuals perceive and evaluate charging infrastructure. Building on these insights, we implement a latent profile analysis to identify probabilistic clusters of EV users who share similar preference patterns. These profiles provide an interpretable basis for capturing behavioral heterogeneity in station selection. Finally, we assess the causal influence of specific treatments (e.g., home charger ownership or certain EV usage patterns) on profile membership. Using inverse propensity score weighting to adjust for observable confounders, we approximate a quasi-experimental design that improves the validity of our inferences.

4.1. Latent Factor Analysis

We build on the broader human-centric framework developed in Reimer et al. [15], which identified key perceptual and behavioral constructs shaping charging infrastructure evaluation across diverse user types. In this study, we focus specifically on current EV users and restrict our analysis to survey items directly related to public charging station selection. This narrower scope allows us to isolate the latent cognitive dimensions that underlie station preferences within this population, and serves as the first step in our multi-stage empirical framework. To reduce the dimensionality of the charging-relevant survey responses (as detailed in Section 3.2.2), we implement a two-stage factor analytic approach. We begin with Exploratory Factor Analysis (EFA) to uncover latent constructs embedded in user preferences, followed by Confirmatory Factor Analysis (CFA) to evaluate the stability and interpretability of the extracted structure across subsamples. This sequence provides the foundation for addressing our first research question (RQ1): what are the underlying dimensions that shape how EV users evaluate and choose public charging stations?

EFA is a data-driven technique widely used to identify patterns of covariance among observed variables in survey data, enabling inference of unobservable latent factors [44]. Its strength lies in its flexibility as it does not impose a predefined structure and can be applied to a broad range of survey contexts, such as ours. The central idea is to explain the observed correlations between items as arising from a smaller set of latent variables, each influencing a subset of questions. Let $\mathbf{X}$ represent the matrix of observed item responses; the method assumes that these responses can be approximated by a linear combination of k latent factors plus residual noise, where $k \ll p$ and p is the number of original variables. We extract latent factors using maximum likelihood estimation with oblique (promax) rotation, allowing factors to correlate, as is often appropriate for behavioral constructs [45]. Items with primary loadings above 0.4 are retained, while those with cross-loadings exceeding 0.3 are removed, in line with common practice in the literature [44]. The number of factors is selected through a combination of Kaiser's criterion (eigenvalues above one), scree plot analysis, and conceptual interpretability of the resulting factors. To ensure the reliability of the extracted

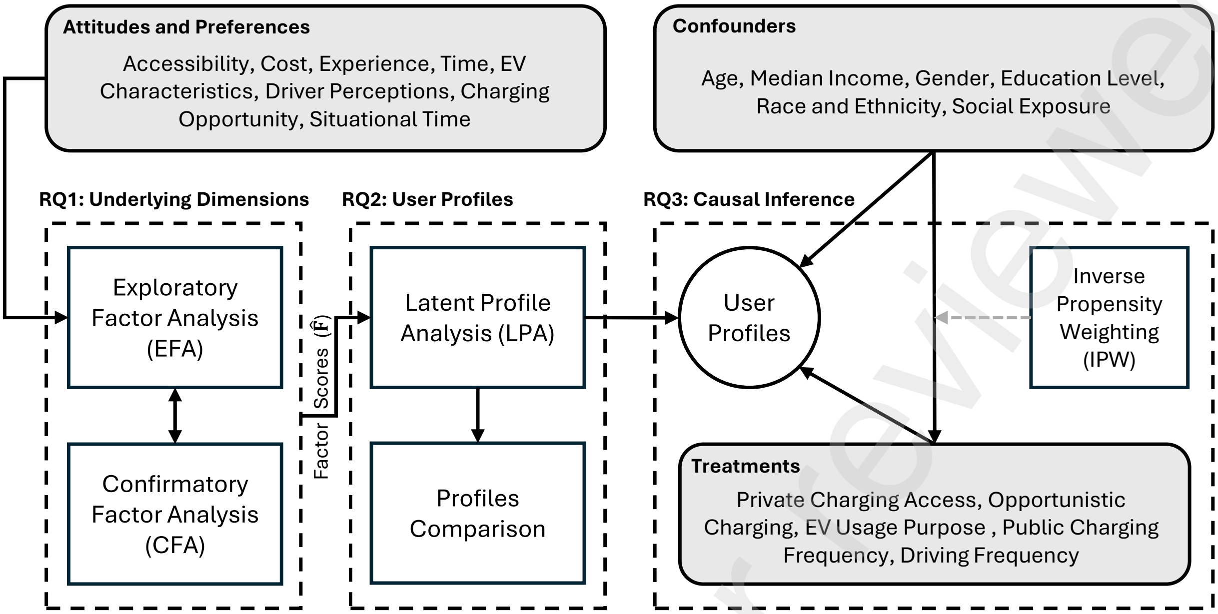

Figure 1: Methodological framework

factors, we calculate Cronbach's alpha (α), a standard measure of internal consistency. Values of α above 0.7 are generally taken to indicate acceptable reliability [46], with higher values reflecting more coherent constructs.

To confirm the robustness of the identified structure, we perform CFA using a randomly drawn hold-out sample [47]. This step tests whether the hypothesized factor model fits the data better than competing structures, including hierarchical or unrestricted models. Model adequacy is often assessed through multiple indices including the Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker–Lewis Index (TLI), with thresholds of RMSEA < 0.06, CFI > 0.95, and TLI > 0.95 indicating good fit [48]. The final factor scores, denoted $\hat{\mathbf{F}}$, serve as low-dimensional summaries of user preferences and form the input for subsequent profiling and causal analysis.

4.2. Latent Profile Analysis

To explore the second research question (RQ2) regarding whether distinct user profiles can be identified based on preferences for public charging stations, we apply Latent Profile Analysis (LPA) to the continuous factor scores $\hat{\mathbf{F}}$ obtained in the previous section. LPA is a person-centered statistical technique designed to uncover unobserved subgroups within a population by grouping individuals who share similar multivariate response patterns [49]. Unlike regression- or variable-centered methods that focus on relationships between measured variables, LPA emphasizes the clustering of individuals and identifies the heterogeneity in preferences and decision-making [49]. Therefore, LPA allows us to construct a typology of users based on their engagement with the latent constructs derived from factor analysis.

LPA assumes that observed responses arise from a mixture of multivariate Gaussian distributions, each corresponding to a latent class or profile. Formally, the observed variance of a given response variable i is decomposed into two components: the between-profile variance due to differences in latent profile means, and the within-profile variance accounting for dispersion around those means. This decomposition is expressed as:

$$\sigma_i^2 = \sum_{k=1}^{K} \pi_k (\mu_{ik} - \mu_i)^2 + \sum_{k=1}^{K} \pi_k \sigma_{ik}^2 \tag{1}$$

where μ_{ik} and σ^2_{ik} denote the mean and variance of variable i within latent profile k, π_k is the proportion of the population in profile k, and μ_i is the overall population mean of variable i. This formulation captures both inter-profile variability and intra-profile dispersion, making LPA well suited to identify hidden behavioral segments across individuals. Each respondent i is assigned to a profile based on the posterior probability of belonging to profile k, given their observed factor scores $\hat{\mathbf{f}}_i$ from the reduced representation matrix $\hat{\mathbf{F}}$. This probability is computed as:

$$\gamma_{ik} = \frac{\pi_k \, \mathcal{N}(\hat{\mathbf{f}}_i \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^{K} \pi_j \, \mathcal{N}(\hat{\mathbf{f}}_i \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)} \tag{2}$$

where $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ represent the mean vector and covariance matrix of profile k, and $\mathcal{N}(\cdot \mid \boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes the multivariate normal density function. Each individual is ultimately classified into a profile using the maximum posterior rule: $c_i = \arg\max_k \gamma_{ik}$.

We estimate model parameters using maximum likelihood, fitting models with $C = 2$ to 6 profiles. Model selection is guided by multiple information criteria, including the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), entropy, and the Lo-Mendell-Rubin adjusted likelihood ratio test [50]. We require each retained profile to account for at least 10% of the total sample to ensure interpretability and avoid overfitting.

4.3. Causal Inference Framework

To identify the determinants that shape EV users' preferences for charging stations (RQ3), we adopt a causal inference framework designed to estimate the effect of specific treatments while adjusting for a set of observed confounders. Unlike conventional regression-based approaches that capture statistical associations without accounting for selection bias, this framework aims to approximate a randomized experimental design by reweighting observations to achieve covariate balance across treatment groups. This adjustment reduces bias due to non-random exposure and enables more credible estimation of directional effects. Our methodological pipeline involves three main steps. First, we define the structure of the causal model by specifying the treatment variable (T), outcome (Y), and a set of confounders (X) for each analysis. Second, we apply inverse propensity score weighting (IPW) to estimate the average treatment effect on the treated (ATT), reweighting observations such that the distribution of covariates becomes balanced across treatment groups. Finally, we estimate the outcome probability through a weighted logistic regression, where the treatment of interest predicts the likelihood of belonging to each latent profile, while accounting for all specified confounders.

4.3.1. Framework Assumptions and Model Setup

In observational studies, individuals are not randomly assigned to treatments. Instead, they self-select based on characteristics that may also influence the outcome of interest. This non-random assignment introduces confounding, as the treatment and outcome may both be driven by shared, potentially unobserved factors [51]. Without proper adjustment, such confounding biases the estimated effects and undermines the validity of causal conclusions. Our framework addresses this by adopting the potential outcomes framework, where each individual i has a hypothetical outcome under treatment, $Y_i(1)$, and under control, $Y_i(0)$. The causal effect is defined as the difference $\tau_i = Y_i(1) - Y_i(0)$, though only one of these is observed. We thus estimate the average treatment effect ATE $= \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$ under three assumptions [51]: (1) treatment assignment is independent of potential outcomes conditional on observed covariates (exchangeability), (2) each individual has a non-zero probability of receiving each treatment (positivity), and (3) an individual's potential outcomes are not affected by the treatment status of others (no interference).

These assumptions allow us to estimate the causal effect of each treatment variable on the outcome while adjusting for a shared set of confounders. Specifically, we model the probability of belonging to a specific charging station preference profile (outcome) as a function of treatment and confounders, estimating separate models for each treatment. This approach is necessary because balancing multiple treatments in a small sample (less than 1,000 observations) can lead to unstable or biased weights.

Outcome The outcome variable in each causal model is the latent profile membership derived from the previous LPA stage. This outcome is categorical and reflects the probabilistic assignment of each respondent to a distinct preference profile. Each respondent is assigned to the profile with the highest posterior probability, allowing us to treat profile membership as a discrete outcome that captures systematic differences in charging station selection behavior.

Confounders Confounders are variables that influence both the treatment and the outcome, potentially biasing the estimated treatment effect if not properly adjusted [51]. We identify confounders based on theoretical relevance and prior empirical literature, ensuring that each is likely to precede the treatment and be related to the outcome. Therefore, based on the available information we include (1) *Age* as older individuals may differ in their charging behavior due to driving habits or income stability. (2) *Median Income* as socioeconomic status influences both EV ownership patterns and access to private infrastructure. (3) *Gender* since behavioral and technological preferences may vary systematically by gender. (4) *Education Level* because higher educational attainment may correlate with environmental attitudes or EV familiarity. (5) *Race and Ethnicity* since disparities in infrastructure access and adoption rates necessitate this adjustment, and (6) *Social treatment to EVs* which is reported as "the number of people you know who own EVs" and acts as a proxy for normative influence and access to informal knowledge.

Treatments Treatments in our framework refer to specific factors that may influence EV users' charging preferences. We construct separate models for each treatment to isolate its effect and avoid complications arising from multiple treatments in limited sample contexts. Each model includes the same outcome and confounders but a different binary or categorical treatment variable. The treatments analyzed include (1) *Private Charger Access* which is a binary indicator for whether the respondent has access to a home or workplace charging point. (2) *Public Charging Frequency* as a categorical measure of how often the respondent uses public stations (weekly, monthly, or less). (3) *Opportunistic Charging Behavior* measured by agreement with the statement "I charge whenever the opportunity arises." (4) *EV Usage Purpose* indicating whether the EV is primarily used for social, commercial, or commuting purposes. (5) *Driving Frequency* as a self-reported metric on how frequently the respondent drives their EV.

Our defined structure allows to quantify how each behavioral or infrastructural factor influences the likelihood of aligning with a given charging station preference profile, yielding targeted insights for interventions and infrastructure planning.

4.3.2. Inverse Propensity Score Weighting (IPW)

To estimate the causal effect of a treatment on profile membership while accounting for differences in confounding variables, we implement inverse propensity score weighting (IPW)[52]. This technique creates a pseudo-population in which the distribution of confounders is similar across exposed and unexposed groups, thereby approximating the conditions of a randomized experiment. Unlike regression-based covariate adjustment or stratification methods, which may not adequately address selection bias or allow for flexible weighting schemes, IPW directly targets imbalance in treatment assignment by assigning higher weights to underrepresented individuals [53]. Under this reweighting, observed differences in outcomes between groups can more plausibly be attributed to the treatment itself, rather than to baseline differences in confounders. This makes IPW especially powerful in complex observational settings such as survey-based behavioral studies [54]. In this study, this method is applied separately for each binary or categorical treatment, ensuring that the balancing condition is met adequately in each model.

The propensity score, defined as the probability of receiving the treatment given observed confounders, is estimated using a logistic regression model. Formally, let $T_i \in \{0, 1\}$ denote the treatment status for individual i, and let X_i be the vector of confounders. The propensity score $\hat{p}_i = P(T_i = 1 \mid X_i)$ is given by:

$$\hat{p}_i = \frac{\exp(\beta_0 + \boldsymbol{\beta}^\top X_i)}{1 + \exp(\beta_0 + \boldsymbol{\beta}^\top X_i)} \tag{3}$$

This equation captures the log-odds of treatment as a linear function of the confounders, with estimated parameters β_0 and $\boldsymbol{\beta}$ derived from the sample. The fitted value $\hat{p}_i$ represents the individual's likelihood of receiving the treatment, conditional on their covariates. Once the propensity scores are estimated, we construct the inverse-propensity weights as follows:

$$w_i = \begin{cases} \frac{1}{\hat{p}_i}, & \text{if } T_i = 1 \quad \text{(Treated)} \\ \frac{1}{1-\hat{p}_i}, & \text{if } T_i = 0 \quad \text{(Untreated)} \end{cases} \tag{4}$$

These weights amplify the influence of individuals whose treatment status is underrepresented relative to their covariates. For example, a participant in the treatment group with a low $\hat{p}_i$ (i.e., who was unlikely to receive the treatment based on their characteristics) will receive a larger weight, reflecting their increased informational value in correcting for selection bias. The reweighted dataset thus simulates a balanced population in which treatment assignment is independent of the covariates.

Overlap Check and Balance Diagnostics A fundamental requirement for valid causal inference using IPW is that the reweighted distribution of covariates is balanced across treatment and control groups [52]. This condition ensures that any differences in outcomes between groups can plausibly be attributed to the treatment, rather than pre-existing differences in observed confounders. To evaluate this, we implement both quantitative and visual diagnostics that assess overlap in propensity scores and balance across covariates. Specifically, we use standardized mean differences (SMDs) to assess covariate balance before and after weighting. The SMD is a scale-invariant measure that quantifies the magnitude of difference in a covariate's distribution between treated and untreated groups [55]. For a binary confounder X_k, such as access to a private charger, the SMD can be computed as:

$$\mathrm{SMD}_k = \frac{p_k^{(T)} - p_k^{(C)}}{\sqrt{p_k^{(T)}(1 - p_k^{(T)}) + p_k^{(C)}(1 - p_k^{(C)})}}, \tag{5}$$

where $p_k^{(T)}$ and $p_k^{(C)}$ represent the weighted proportions of individuals with the characteristic in the treated ($T = 1$) and control ($T = 0$) groups, respectively. This formulation is equivalent to a standardized effect size using a pooled binomial variance, and values of $|\mathrm{SMD}_k| < 0.2$ are typically considered indicative of acceptable balance [55].

4.3.3. Weighted Outcome Analysis

With covariate distributions balanced through IPW, the final step estimates the causal effect of each treatment variable on the probability of profile membership. The reweighted sample mimics a randomized experiment in which the treated and untreated groups are comparable on all observed confounders. Thus, any observed differences in the outcome can be interpreted as resulting from differences in the treatment alone [56]. To quantify this effect, we estimate a weighted logistic regression model, where the outcome is profile membership and the weights are derived from the propensity score model.

$$\mathrm{logit}(P(Y_i = 1)) = \alpha + \tau T_i, \tag{6}$$

where Y_i denotes whether individual i belongs to the profile of interest, and $T_i \in \{0, 1\}$ indicates treatment status (e.g., access to a private charger). The coefficient τ captures the log odds of being in the specified profile for the treated group relative to the control group. Because the treatment groups are balanced on observed confounders, τ represents an unbiased estimate of the average treatment effect on the treated (ATT) [54].

Further, the exponentiated coefficient e^τ yields the causal odds ratio, indicating how much more likely a treated individual is to belong to the given profile compared to a similar untreated individual. For instance, if $e^\tau = 2$, then individuals with access to a private charger are twice as likely to exhibit behavioral characteristics aligned with a particular charging station selection profile compared to those without such access, holding all else equal. This weighted regression is applied independently for each treatment, using the appropriate profile-specific outcome and inverse probability weights.

5. Results

We present our findings in three parts, each corresponding to a central research question. We begin by identifying latent dimensions that structure how EV users evaluate charging stations, revealing core factors related to perceived convenience, cost sensitivity, and station reliability. Building on these dimensions, we use LPA to uncover distinct user groups who share similar charging selection preferences, offering a typology of EV users based on their selection behavior. Finally, we move beyond description to causation, applying IPW to estimate the influence of various factors on profile membership. This allows us to disentangle how certain conditions and behavioral routines shape selection strategies, advancing a more actionable understanding of charging infrastructure usage.

5.1. Deconstructing the Dimensions of Charging Station Preferences

EV users evaluate public charging stations not only by comparing tangible station-level attributes, such as cost or charging speed, but also through broader cognitive frameworks shaped by personal attitudes and situational constraints. Prior work emphasizes this distinction between choice attributes directly observed at the point of decision and the contextual factors that shape how these decisions are cognitively framed [15]. To operationalize this conceptual separation, we conducted two separate EFAs based on responses to the survey prompt: "Imagine you are looking for a charging station for your electric vehicle. Which of the following characteristics or features would be important to you when choosing a charging station?" The first group of 23 items focused on infrastructure, cost, and time-related attributes as elements that define the comparative appeal of one station over another. The second group comprised 21 items capturing individual characteristics, perceptions, and situational considerations that influence decision-making at a broader cognitive level. In both groups, item correlations were moderate to high, ranging from 0.31 to 0.74, indicating a coherent latent structure. The Kaiser-Meyer-Olkin (KMO) measure, which assesses sampling adequacy by quantifying the proportion of variance among variables that might be common variance, was 0.85 and 0.90 for the two groups, respectively. This is well above the acceptable threshold of 0.70 for moderate-sized samples [44]. Bartlett's test of sphericity confirmed that the correlation matrices were suitable for factor analysis ($p < 0.001$) [44].

Parallel analysis and visual inspection of scree plots in Figure 2 guided the number of latent factors. The distinct break in the slope of each scree plot, which represents the relationship between eigenvalues and the ordinal number of factors, was used as a reference point to determine the number of meaningful latent constructs to retain [57]. For the infrastructure-cost-time group, we retained five factors. In the situational-characteristics group, we retained three factors, despite the scree plot suggesting a fourth. This decision was made due to the lack of conceptual coherence in the additional factor, which included only a single item with significant loading (> 0.30). Collectively, the retained factors explained approximately 70% of the variance in the data. These decisions are consistent with best practices in factor retention, which emphasize balancing statistical criteria with the interpretability and theoretical relevance of the extracted factors.

To validate the factor structure, we conducted a confirmatory factor analysis (CFA) on a hold-out subsample ($N = 365$). The final model, comprising seven factors across both groups, exhibited acceptable fit with $RMSEA = 0.054$, $SRMR = 0.077$, $TLI = 0.823$, and $CFI = 0.838$. Although the TLI and CFI fell slightly below conventional thresholds, these values are within acceptable bounds given the multidimensionality of the model and the diversity of included items. The extracted factor scores from this validated structure form the basis for the subsequent latent profile analysis. Results for the full survey ($N = 997$), including other vehicle ownership types such as PHEVs and non-EVs, are reported in Reimer et al. [15].

We retained only those items with primary factor loadings above 0.30, in line with conventions in literature, recommending thresholds between 0.30 and 0.40 to ensure interpretability and relevance of latent constructs [44]. The internal consistency of each factor was assessed using Cronbach's alpha (α), a widely accepted measure of reliability. Values of α around 0.70 to above are generally considered acceptable [46], indicating that the items within each factor measure a coherent underlying concept. All factors exceeded this threshold, with alphas ranging from 0.68 to 0.85. The final set of eight latent factors, along with their corresponding items, is presented in Table 2. These factors reflect the multidimensional nature of EV users' charging station evaluations, integrating both infrastructure-facing and user-centric considerations. Specifically:

F1 Infrastructure & Perceived Trust: This factor includes 7 items with loadings ranging from 0.31 to 0.80. It captures perceptions of technological and institutional reliability, such as the energy source of the charging station, vehicle-to-grid (V2G) capabilities, battery swapping, valet services, and trust-related signals including recommendations and user reviews. These items reflect not only functional evaluations but also broader trust-based heuristics that shape charging station selection [13, 14, 29, 33].

F2 Time & Travel Constraints: Comprising 5 items with loadings between 0.45 and 0.74, this factor reflects concerns related to time efficiency and logistical burden. It includes waiting time, idle time, total travel time, and detour distance. This factor aligns with established findings that time cost and charging delays are major barriers to EV adoption and station selection [11, 30, 34].

F3 Accessibility & Charging Speed: This factor contains 5 items with loadings from 0.30 to 0.63. It emphasizes physical accessibility and functional utility, including availability of charging piles, perceived ease of use, charging speed, and past satisfaction. These elements have consistently been linked to infrastructure usability and likelihood of repeat visitation [9, 12, 14].

F4 Charging & Parking Costs: Includes 4 items with loadings from 0.42 to 0.70, centered on economic considerations such as price transparency, cost of charging, parking fees, and perceived savings. This cost-focused dimension is widely recognized in literature as a key determinant of consumer behavior in charging networks [10].

F5 Charging Amenities & Activities: Composed of 2 items with high loadings (0.67 and 0.87), this factor reflects co-located services such as shopping and dining options that enhance the perceived value of dwell time. While often underrepresented in infrastructure planning models, this dimension supports findings that multifunctional environments increase station attractiveness [11, 36].

F6 Situational Awareness: Encompassing 7 items with loadings between 0.35 and 0.77, this factor includes indicators such as the number of household vehicles, daytime versus nighttime usage, seasonality, and weekday behavior. These reflect routine-specific decision contexts that are typically overlooked in conventional charging models but are increasingly recognized as crucial to understanding usage variability [23, 32, 37].

F7 Charging Awareness & Usage Patterns: Consisting of 8 items with loadings from 0.30 to 0.60, this factor captures familiarity with infrastructure availability and habitual charging behaviors. It includes station density, proximity, availability at home or work, and driving schedules, pointing to spatial and behavioral accessibility beyond physical distance [9, 21].

F8 EV Characteristics: Comprising 4 items with loadings between 0.50 and 0.60, this factor relates to technical features that constrain charging decisions, including battery range, current state of charge, EV type, and self-charging capabilities. These items provide a necessary baseline for evaluating how vehicle-specific limits shape charging opportunities [12, 31].

These eight factors provide a structured and interpretable basis for understanding EV users' charging preferences beyond simple station-level attributes. Factors F1 through F4 capture traditional infrastructural and economic considerations widely cited in the literature, reaffirming the importance of reliability, speed, accessibility, and cost. Meanwhile, F5 through F8 surface less frequently studied but critical dimensions. For instance, F5 highlights the overlooked role of amenities in enhancing user satisfaction during dwell times, offering new insights for station co-location strategies. F6 and F7 point to the cognitive framing of decision-making, shaped by daily routines and spatial knowledge—features often absent from current accessibility models. F8 reaffirms that EV-specific constraints are nontrivial in shaping charging decisions.

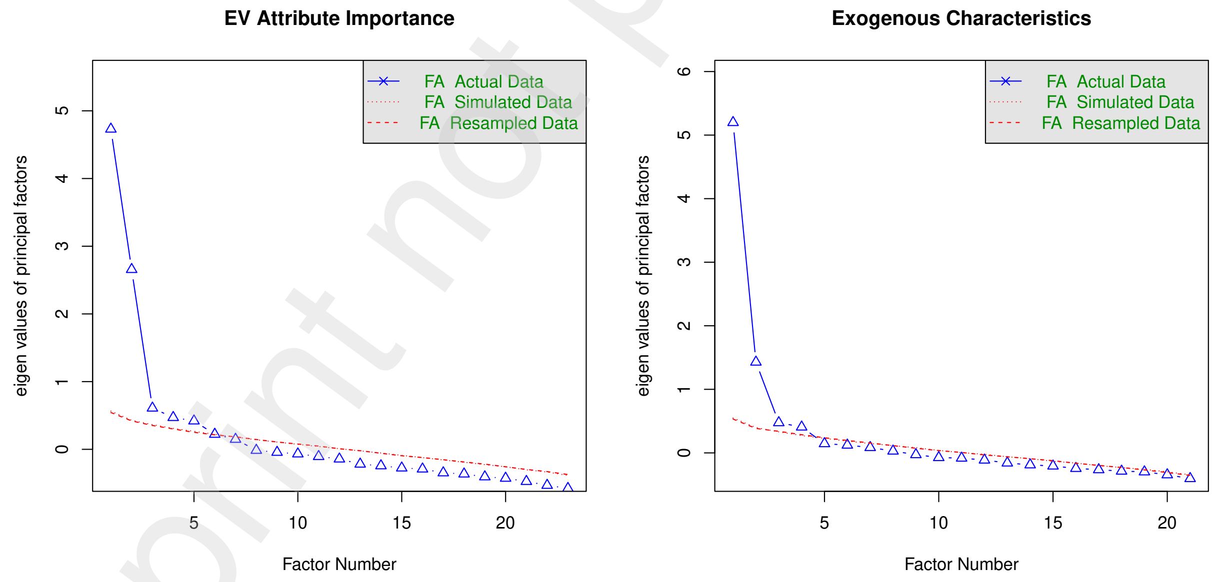

Figure 2: Latent factors scree plot

5.2. Segmenting Charging Station Selection Preferences

To capture heterogeneity in how individuals evaluate PCSs, we applied LPA to the eight latent factors identified in the previous section. While EFA transformed individual survey responses into a smaller set of underlying latent

Abbr.	Variables	F1	F2	F3	F4	F5	F6	F7	F8
ATT1	Energy source of power station	0.731							
ATT2	Charging network provider	0.349							
ATT3	Vehicle-to-grid (V2G) capabilities	0.803							
ATT4	Battery swapping/switching	0.792							
ATT5	Amenities					0.866			
ATT6	Opportunities for other activities during charging					0.669			
ATT7	Accessibility of charging station			0.626					
ATT8	Location area of charging station			0.456					
ATT9	Available sockets/piles (#)			0.445					
ATT10	Charging cost				0.654				
ATT11	Price savings				0.446				
ATT12	Parking cost				0.701				
ATT13	Perfect information (about price)				0.423				
ATT14	Previous satisfaction			0.317					
ATT15	Recommendations by friends and family	0.478							
ATT16	Reviews	0.313		0.305					
ATT17	Valet-charging	0.722							
ATT18	Charging duration		0.446						
ATT19	Charging speed			0.369					
ATT20	Detour distance/travel time		0.535						
ATT21	Travel Time		0.558						
ATT22	Waiting time (min)		0.490						
ATT23	Idle time at charging station		0.739						
EXO2	State of charge (%)								0.508
EXO1	EV type								0.538
EXO3	Battery/driving range (mile)								0.600
EXO4	Self-charging								0.501
EXO5	Range anxiety							0.474	
EXO6	Driver risk attitudes						0.372		0.386
EXO7	Environmental consciousness						0.447		
EXO8	Awareness of charging infrastructure							0.404	
EXO9	Home charging availability (garage)							0.455	
EXO10	Number of charging stations							0.604	
EXO11	Workplace charging availability						0.473		
EXO12	Distance between charging stations							0.420	
EXO13	Availability on your way							0.353	
EXO14	Number of household vehicles						0.690		
EXO15	Frequency of charging events						0.307	0.309	
EXO16	Remaining distance to destination						0.770		
EXO17	Daytime/night						0.426		
EXO18	Driving schedule						0.349	0.365	
EXO19	Dwelling time at destination						0.311	0.356	
EXO20	Number of daily trips						0.544		
EXO21	Season						0.753		
Cronbach's α		0.83	0.76	0.68	0.71	0.78	0.85	0.77	0.69
SS Loadings		2.985	1.750	1.465	1.456	1.413	3.179	1.823	1.518
Proportion Var		0.130	0.076	0.064	0.063	0.061	0.151	0.087	0.072
Cumulative Var		0.130	0.206	0.270	0.333	0.394	0.545	0.632	0.704
KMO				0.85				0.90	

Table 2
Rotated factor loadings and explained variance for infrastructure and perceptual constructs (F1–F5) and EV characteristic and situational constructs (F6–F8).

constructs, LPA extends this by classifying individuals into subgroups that share similar combinations of preferences and attitudes across those constructs. This enables us to identify distinct profiles of EV users based on their prioritization of charging-related factors. These profiles later serve as the dependent outcome in our causal inference framework.

LPA was estimated using a Gaussian finite mixture model and the Expectation-Maximization (EM) algorithm. Prior to estimation, factor scores were standardized to ensure comparability across dimensions. Models with two to six profiles were fitted, and model fit was evaluated using the Bayesian Information Criterion (BIC), entropy,

# Profiles	BIC	Entropy	Percent Uncertain	Smallest Profile Size (%)
2	-7354.285	0.870	0.082	23.6%
3	-7364.594	0.697	0.301	24.9%
4	-7359.838	0.732	0.299	13.7%
5	-7360.163	0.771	0.299	9.3%
6	-7392.323	0.780	0.312	7.1%

Table 3
Model fit statistics for Latent Profile Analysis (LPA) across 2 to 6 profiles. The smallest profile size is normalized by dividing by 365.

and classification uncertainty. The latter was operationalized as the percentage of respondents with posterior profile membership probabilities below 0.80. As shown in Table 3, the BIC has an overall downward trend with increasing profiles, a known behavior of this criterion due to its sensitivity to added model complexity, as each additional profile increases the model's ability to explain variation in the data. However, the two-profile solution achieved the most interpretable segmentation with high entropy (0.87) and low uncertainty (8.2%), and it avoided overly small classes that compromise practical relevance. We therefore selected the two-profile VVE model (ellipsoidal, equal orientation) as our final solution.

The two profiles, labeled P1 (n = 279, 76.4%) and P2 (n = 86, 23.6%), exhibit distinct prioritization patterns across the eight factors (Table 4 and Figure 3). These factor scores represent standardized values computed across the full sample, where positive means indicate above-average prioritization of the corresponding latent construct relative to the overall population, negative means indicate below-average prioritization, and values near zero suggest neutral or average emphasis. While P1 members display low or near-zero mean scores across most factors, P2 members show consistently elevated scores, especially on factors related to infrastructure perception (F1), contextual awareness (F6), and vehicle characteristics (F8). These patterns suggest qualitatively different approaches to PCS selection.

P1 Efficiency-Oriented Users: This group comprises the majority (76.4%) of respondents and is characterized by lower importance ratings on six of the eight factors, except accessibility (F3) and cost considerations (F4). Their strongest negative deviations appear in F1 (Infrastructure & Perceived Trust, mean = −0.34) and F6 (Situational Awareness, mean = −0.27). Members of this group appear to place minimal emphasis on external validation (e.g., trust signals or amenities), contextual routines, or technical constraints. This aligns with findings that some EV users adopt a utilitarian or default-based approach to charging, particularly when home charging reduces dependence on PCS environments [58]. The tight clustering of interquartile ranges also suggests a relatively homogenous profile.

P2 Information-Responsive Users: Representing 23.6% of users, this group exhibits positive scores on five factors, particularly in F1 (mean = 1.09), F5 (Charging Amenities, mean = 0.35), F6 (Situational Awareness, mean = 0.86), and F8 (EV Characteristics, mean = 0.08). These respondents demonstrate higher awareness of both the built environment and their own technical needs, integrating contextual signals such as time-of-day, station amenities, and vehicle constraints into their selection process. This preference structure mirrors behavior documented in studies of experience-based decision-making among advanced EV users [59].

The two profiles capture a meaningful segmentation of EV users based on charging station preferences. The majority (P1) reflect a more infrastructure-independent approach focused on accessibility and cost, potentially indicating reliance on private chargers or a lower frequency of public charging. In contrast, the smaller but distinct subgroup (P2) exhibits context-aware and preference-sensitive decision strategies, suggesting a need for richer, amenity-supported infrastructure. These findings underscore the importance of tailoring charging infrastructure not only to technical demand but also to the informational and experiential cues users rely on. For policymakers and planners, these results suggest that one-size-fits-all deployment strategies may fail to engage key user segments, particularly those motivated by nearby amenities or situational compatibility.

Figure 4 compares the sociodemographic composition of the two latent profiles. While both groups exhibit similar gender distributions, with males comprising approximately 60% of each profile, differences emerge across other categories. In terms of education, P2 (*Information-Responsive Users*) shows a substantially higher share of graduate degree holders (48%) compared to P1 (*Efficiency-Oriented Users*, 33%). A similar divide is seen in income where

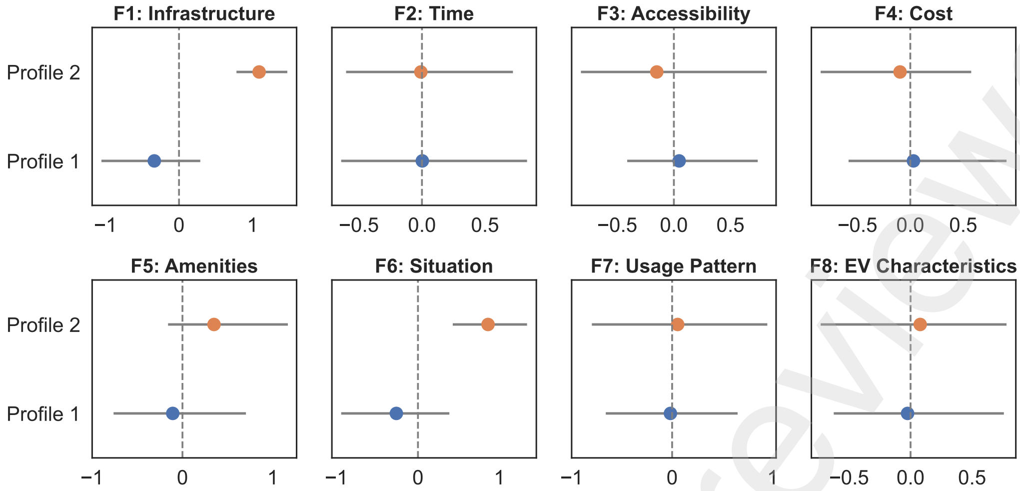

Figure 3: Latent factors distribution for charging station selection profiles.

Profile	F1 Infrastructure	F2 Time	F3 Accessibility	F4 Cost	F5 Amenities	F6 Situation	F7 Usage Patterns	F8 EV Characteristics
1	-0.336 (0.870)	0.003 (1.024)	0.047 (0.954)	0.030 (1.021)	-0.108 (1.014)	-0.265 (0.944)	-0.017 (0.971)	-0.024 (1.007)
2	1.090 (0.483)	-0.009 (0.925)	-0.151 (1.129)	-0.097 (0.927)	0.349 (0.870)	0.861 (0.625)	0.055 (1.093)	0.078 (0.978)

Table 4
Mean and standard deviation of factor scores (F1 to F8) across LPA profiles. Standard deviations are shown in parentheses.

44% of P2 members report annual incomes below \$75,000, whereas P1 includes a higher proportion of individuals in the upper income bracket (42% earn above \$110,000). Racial and ethnic composition also diverges sharply, with P2 containing a higher proportion of Black respondents (41%) and fewer White respondents (48%) compared to P1 (19% and 60%, respectively). Nevertheless, political affiliation displays the most distinct contrast. while 63% of P1 identify as liberal, 51% of P2 identify as conservative. Overall, these patterns suggest that P1 users are more likely to be affluent, White, and politically liberal, with lower levels of educational attainment. In contrast, P2 users tend to be higher educated yet lower income, more racially diverse, and more politically conservative than their P1 counterparts. These contrasts suggest that sociodemographic characteristics are associated with how individuals prioritize features of public charging infrastructure, consistent with prior work in this field [37].

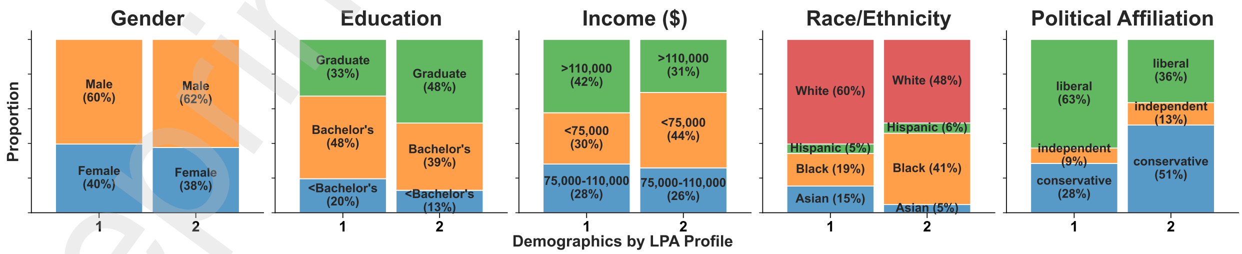

Figure 4: Comparison of profiles by demographic.

5.3. Causal Drivers of Charging Station Selection Preferences

To answer our third research question (RQ3) *what are the key behavioral and infrastructural drivers that explain why EV users differ in their selection of public charging stations*, we estimate the causal impact of a set of treatment variables on profile membership. In specific, we focus on five treatment variables. First, *access to a private charger* (home or workplace) is considered a key determinant of reliance on public charging infrastructure, with prior studies finding that users with private access are less sensitive to the physical and operational features of public stations [58]. Second, we consider *opportunistic charging behavior* defined as whether users tend to charge in small quantities whenever an opportunity arises, as it reflects responsiveness to short-term availability. Third, we examine the *primary purpose of EV usage*, whether for social, business, or commuting needs. These categories are not mutually exclusive but serve as contextual indicators of variability in charging motivations. Fourth, *driving frequency* provides a proxy for overall usage intensity, which may interact with the perceived importance of certain station attributes. Finally, we include *public charging frequency* (weekly or monthly) to assess how the extent of reliance on public infrastructure may condition selection preferences.

Using LPA profile membership as a revealed outcome of charging station preferences, we estimate the effect of each treatment variable using the inverse propensity weighting (IPW) framework described in Section 4. Propensity scores are estimated using logistic regression models of the form $T_i \sim X_i$, where T_i is the binary treatment variable and X_i is the vector of confounders including age, income, education, race, gender, and social treatment to EVs. Each observation is then reweighted using inverse-propensity weights to achieve covariate balance across treatment groups. We then fit a weighted logistic regression model of the form $Y_i \sim T_i$, where Y_i is a binary indicator of profile membership (1 if the user belongs to P2, 0 otherwise), to estimate the causal effect of the treatment on the likelihood of belonging to the Information-Responsive user group. This approach allows us to isolate the directional influence of behavioral and infrastructural factors on the formation of distinct user profiles, yielding interpretable and causal estimates of how access, habits, and purpose shape charging preferences.

Table 5 summarizes the results of logistic regression models used to estimate the propensity scores for each treatment, including binary indicators for private charger access, opportunistic charging, public charging frequency (weekly and monthly), EV driving frequency (weekly and monthly), and three non-mutually-exclusive EV usage purposes (social, business, and commuting). As expected in propensity score modeling, the goal is not to maximize explanatory power or ensure all predictors are statistically significant, but rather to generate scores that allow for covariate balancing between treated and control groups [53]. Nevertheless, several covariates emerge as statistically significant predictors of specific treatments, reinforcing their role as important confounders in the causal framework. Social treatment to EVs (measured by the number of known EV users) is positively associated with private charger access ($p < 0.05$), commuting as a driving purpose ($p < 0.05$), and business use ($p < 0.1$), suggesting that normative influence and peer networks may facilitate access to infrastructure and shape usage contexts. Age is negatively associated with public charging frequency ($p < 0.01$ for weekly users), indicating that younger users are more likely to rely on public infrastructure and possibly reflecting differences in housing type, commute behavior, or early adoption patterns. In terms of income, lower-income users are more likely to report business-related driving ($p < 0.05$), while higher-income users are marginally less likely to engage in commuting-related EV use ($p < 0.1$). Importantly, these variables serve not as direct drivers of profile membership in our causal models, but as confounders that must be accounted for to isolate the effects of the treatment variables of interest. Furthermore, we report the overall fit statistics (AIC, BIC, and log-likelihood) vary across models, with AIC values ranging from 371.75 to 744.50 and log-likelihoods between 416.61 and 847.21, indicating acceptable model performance for score generation purposes.

To assess whether the overlap assumption holds, we examine the distribution of propensity scores across the two outcome groups (profile 1 and profile 2). The absence of extreme weights in the estimation process indicates that no major violations of the overlap condition are present. This conclusion is further supported by post-weighting diagnostics, which show that standardized mean differences (SMDs) between treated and control groups for all covariates fall below 0.13. These values are well below the commonly accepted threshold of 0.2, indicating that covariate distributions are successfully balanced after applying inverse-propensity weights.

In the final stage of the causal analysis, we estimate a series of weighted logistic regression models to assess how each treatment variable influences the probability of belonging to Profile 2 (*Information-Responsive Users*), using Profile 1 (*Efficiency-Oriented Users*) as the reference category. Each model uses the same outcome variable and set of confounders, but includes a different treatment variable. The outcome is a binary indicator of profile membership, and the sample is weighted using inverse-propensity scores derived from the models described in Table 5. The results of these weighted regressions are summarized in Table 6, which reports coefficient estimates, standard errors, and

	Private Charging	Opportunistic Charging	Driving Purpose: Social	Driving Purpose: Business	Driving Purpose: Commuting	PECSfreq: Monthly	PECSfreq: Weekly	EVfreq: Monthly	EVfreq: Weekly
Intercept	-0.227	-0.134	0.382	-1.461	**1.898***	0.110	0.624	**1.798***	0.723
	(0.789)	(0.713)	(0.804)	(0.774)	(0.821)	(0.876)	(0.916)	(0.912)	(1.052)
PeopleEVdrive [T.1]	**1.173***	0.711	0.085	0.854	**1.023***	0.341	-0.389	-0.741	-0.409
	(0.481)	(0.461)	(0.533)	(0.556)	(0.499)	(0.600)	(0.582)	(0.627)	(0.742)
PeopleEVdrive [T.2]	**1.384****	0.885	0.388	**1.255***	0.746	0.774	0.136	-0.309	-0.020
	(0.473)	(0.453)	(0.527)	(0.549)	(0.480)	(0.590)	(0.569)	(0.622)	(0.733)
Income [<75k$]	-0.017	0.041	-0.023	**0.620***	-0.235	-0.201	0.129	0.284	0.187
	(0.327)	(0.309)	(0.341)	(0.305)	(0.375)	(0.380)	(0.399)	(0.366)	(0.416)
Income [>110k$]	0.538	-0.160	-0.052	0.124	**-0.678**†	-0.484	**-0.661**†	0.528	0.025
	(0.348)	(0.297)	(0.331)	(0.291)	(0.354)	(0.345)	(0.387)	(0.366)	(0.404)
Gender [Male]	-0.128	0.057	0.088	0.361	-0.198	**0.607***	**0.521**†	0.108	0.044
	(0.278)	(0.241)	(0.268)	(0.239)	(0.283)	(0.286)	(0.311)	(0.296)	(0.335)
Degree [Graduate]	0.151	-0.222	-0.217	0.109	0.078	0.136	0.497	**0.701***	0.231
	(0.310)	(0.263)	(0.287)	(0.254)	(0.306)	(0.308)	(0.338)	(0.334)	(0.372)
Degree [<Bachelor's]	-0.279	-0.285	0.390	**-0.787***	-0.424	0.013	0.052	0.113	**-0.821**†
	(0.357)	(0.336)	(0.396)	(0.347)	(0.384)	(0.406)	(0.436)	(0.394)	(0.481)
Race [Black]	-0.174	0.340	-0.178	**0.914***	-0.447	**1.562****	**1.998*****	0.091	-0.670
	(0.448)	(0.393)	(0.422)	(0.397)	(0.485)	(0.521)	(0.557)	(0.473)	(0.560)
Race [Hispanic]	0.478	0.500	-0.289	-0.039	0.211	1.061	1.142	0.030	**1.411**†
	(0.751)	(0.599)	(0.623)	(0.608)	(0.770)	(0.724)	(0.795)	(0.831)	(0.819)
Race [White]	0.264	**0.593**†	0.523	0.120	-0.129	0.442	0.400	0.535	0.492
	(0.419)	(0.354)	(0.395)	(0.354)	(0.442)	(0.403)	(0.462)	(0.440)	(0.485)
Age	0.001	-0.005	0.009	-0.013	-0.016	**-0.028***	**-0.039****	**-0.035****	-0.014
	(0.012)	(0.010)	(0.012)	(0.010)	(0.011)	(0.012)	(0.013)	(0.012)	(0.014)
AIC	379.00	456.01	392.08	467.40	371.75	744.50		739.77	
BIC	423.87	500.88	436.95	512.27	416.61	847.21		842.48	
Log Likelihood	-177.50	-216.01	-184.04	-221.70	-173.87	-350.25		-335.89	
No. Observations	348	348	348	348	348	348		348	

Table 5
Logit and multinomial logit regression results for behavioral outcomes related to EV charging. Coefficients are in bold when statistically significant at the 10% level or better. Standard errors are shown in parentheses.

Note: **Bolded** coefficients are statistically significant. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

model fit statistics for all treatments considered. AIC values range from 362.34 to 391.02 and log-likelihood values are between -178.17 and -193.30. These fit metrics suggest that the weighted models adequately capture variation in profile membership driven by each treatment variable, particularly for those with strong behavioral or infrastructural relevance.

The model for *private charging access* shows a statistically significant positive association with Profile 2 membership ($p < 0.05$), with an odds ratio of 2.39. This indicates that users with private home or workplace charging access are more than twice as likely to exhibit preference patterns characterized by attention to infrastructure provider characteristics (e.g., network branding, energy source), the availability of nearby amenities (e.g., retail or dining options), temporal and spatial situational constraints (e.g., time of day, distance to stations), and compatibility with EV-specific needs (e.g., battery range, state of charge). This finding suggests that users with private charging access may have more flexibility to prioritize attributes such as convenience, context, and system compatibility, likely because their reliance on public infrastructure is more discretionary than constrained.

In contrast, the model for *opportunistic charging* behavior, defined as charging in small amounts whenever the opportunity arises, does not show a statistically significant association with profile membership ($p = 0.41$). This suggests that opportunistic charging tendencies alone do not meaningfully influence how individuals prioritize public charging station attributes such as provider reliability (F1), nearby amenities (F5), or situational compatibility (F6). These results imply that broader charging routines or structural factors may play a larger role than spontaneous behavior in shaping stated preferences for PCS features.

Among the *driving purposes*, EV use for *business* purposes is significantly associated with Profile 2 membership ($p < 0.001$, OR = 2.70), indicating that these users are more likely to report preferences emphasizing infrastructure trustworthiness, time compatibility, and vehicle-specific constraints. This likely reflects the higher opportunity costs

	Private Charging	Opportunistic Charging	Driving Purpose			PECSfreq		EVfreq	
			Social	Business	Commuting	Monthly	Weekly	Monthly	Weekly
Intercept	**-1.836*****	**-1.030*****	**-0.882*****	**-1.628*****	**-0.554***	**-2.629*****	**-2.629*****	**-1.455*****	**-1.455*****
	(0.325)	(0.213)	(0.243)	(0.193)	(0.241)	(0.391)	(0.391)	(0.297)	(0.297)
LPA Profile	**0.872***	-0.150	-0.330	**0.993*****	**-0.761****	**1.768*****	**2.006*****	0.457	0.298
	(0.352)	(0.263)	(0.283)	(0.257)	(0.283)	(0.433)	(0.441)	(0.341)	(0.384)
AIC	383.90	388.60	389.60	375.52	385.99	362.34		391.02	
BIC	391.12	395.82	396.82	382.74	393.21	372.99		401.67	
Log Likelihood	-189.95	-193.30	-192.80	-185.76	-189.99	-178.17		-192.51	
No. Observations	348	348	348	348	348	348		348	

Table 6

Logit regression results with odds ratios for the effect of charging and usage behavior on LPA profile membership. Coefficients are followed by standard errors in parentheses and odds ratios beneath.

Note: **Bolded** coefficients are statistically significant. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

and time sensitivity associated with work-related travel, where disruptions due to unclear pricing, limited charging speed, or station unavailability can have direct professional or financial consequences. As such, business users may demand more reliable and well-signposted infrastructure with predictable performance, underscoring the role of station quality, service integration, and dependability in supporting commercial EV operations. By contrast, EV use for *commuting* is negatively associated with Profile 2 ($p < 0.01$, OR = 0.47), suggesting that commuters tend to de-emphasize features such as the availability of amenities at or near the station (F5), infrastructure-related cues like provider branding and energy source (F1). Instead, their preferences appear to prioritize predictability, minimal charging and parking cost, and pricing information. This aligns with the efficiency-oriented pattern of Profile 1, which reflects a narrower set of practical considerations optimized for regular, goal-driven trips. The model for *social* use of EVs is not statistically significant ($p = 0.25$), indicating that leisure or personal activities do not systematically predict stated preferences in charging station evaluation.

Charging frequency emerges as one of the strongest predictors in the model. Public charging on a *monthly* basis is significantly associated with Profile 2 membership ($p < 0.001$, OR = 5.86), as is *weekly* public charging ($p < 0.001$, OR = 7.43). These users place greater emphasis on features such as the availability of charging piles, station accessibility, and charging speed (F3), trust-related indicators like provider reputation and user reviews (F1), and compatibility with personal schedules and trip characteristics (e.g., time of day, weekday vs. weekend use, and station proximity along common routes) captured in F6. The strong association suggests that repeated engagement with public infrastructure may heighten users' sensitivity to the reliability, efficiency, and convenience of stations. This supports the idea that frequent users develop more refined expectations regarding station performance, such as anticipating wait times, valuing amenities during dwell time, or selecting stations based on routine compatibility. This highlights the role of learned experience in shaping public charging preferences. In contrast, self-reported *driving frequency* (weekly or monthly) does not have a significant association with profile membership ($p = 0.12$ and $p = 0.27$, respectively). This suggests that it is not how often individuals drive their EVs, but rather how often they rely on public charging that drives differences in preference profiles.

These findings indicate that frequent public charging and business-related EV use are strong drivers of preference structures aligned with Profile 2, marked by attention to trust in infrastructure providers, temporal flexibility, nearby services, and EV compatibility. In contrast, users with commuting-oriented usage patterns or lower public charging frequency are more likely to fall into Profile 1, which reflects a narrower prioritization of charging considerations. From a planning perspective, this highlights the importance of designing a charging infrastructure that is sensitive to users' functional contexts and public charging dependence. These findings suggest that infrastructure planning should prioritize improving the quality and usability of public charging stations for frequent users by ensuring consistent availability, minimizing wait times, and co-locating services that enhance the value of time spent at the station. Such improvements can better align with the expectations of experienced users who rely on public charging as part of their routine mobility and may increase overall satisfaction and system efficiency.

6. Discussion & Conclusion

The rapid expansion of EV infrastructure has underscored the need for a deeper understanding of how users evaluate and select public charging stations. Despite considerable progress, major gaps persist in the literature regarding the multidimensional nature of charging station preferences, the segmentation of EV users based on these preferences, and the factors driving heterogeneity in station selection strategies. Addressing these gaps, this study integrates a behavioral factor analysis, user profiling, and causal inference framework based on a detailed survey of BEV owners. Through factor analysis, we uncover eight latent dimensions that capture how EV users evaluate public charging options, moving beyond a narrow focus on cost and speed to include infrastructure-related signals, situational routines, and EV-specific technical constraints. Building on these factors, we apply LPA to identify two distinct user segments, demonstrating that charging station selection behavior is not uniform and requires targeted infrastructural responses. Finally, using inverse propensity weighting, we estimate the causal effects of private charging access, charging behavior, EV usage purpose, and reliance on public infrastructure on profile membership, offering actionable insights into the behavioral and infrastructural drivers of charging selection heterogeneity. These findings have critical implications for infrastructure planning, emphasizing that expanding network coverage alone may be insufficient if user-specific informational, contextual, and technical needs are not simultaneously addressed. We summarize our main findings below.

Finding 1: *EV users evaluate public charging stations based on a wide array of factors beyond cost and charging speed, including confidence in station reliability, situational convenience, and access to amenities.*

This finding emerges from our factor analysis, which extracted eight latent constructs from 44 survey items. While well-studied operational concerns like charging speed and cost (F3, F4) remain central, users also prioritized factors such as the charging provider, co-located services, and compatibility with situational needs (F1, F5, F6). This highlights the need for charging station planning to move beyond minimal technical specifications. Infrastructure development should consider the integration of nearby amenities such as retail and dining opportunities, improve informational transparency regarding pricing, real-time availability, and station operational status, and support context-sensitive user experiences by offering features like flexible access during peak travel times to meet evolving expectations.

Finding 2: *EV users can be segmented into two distinct profiles based on charging station selection patterns: Efficiency-Oriented Users and Information-Responsive Users.*

Using LPA on the extracted factor scores, we identified two behavioral groups with fundamentally different prioritization strategies. Efficiency-Oriented Users place relatively lower importance on infrastructure provider attributes (e.g., network reliability, energy sourcing) and situational cues (e.g., time-of-day suitability, travel detour burden), whereas Information-Responsive Users weigh opportunities to engage in nearby amenities, alignment with personal schedules, and compatibility with EV-specific charging needs (e.g., battery range) heavily. This segmentation highlights that uniform infrastructure strategies, such as deploying standardized charging sites without considering co-located activities or flexible access risk not satisfying charging needs of certain EV user segments. Planning approaches must therefore anticipate differentiated expectations, providing not only technical capacity but also user-centric enhancements to ensure stations meet the diverse practical, contextual, and experiential needs of EV drivers.

Finding 3: *Access to private home or workplace charging substantially shifts public charging preferences toward more selective, experience-based evaluation.*

From our IPW analysis, users with private charging access were over twice as likely to belong to the Information-Responsive profile. This finding underscores that access to private charging not only reduces reliance on public stations but also reshapes user expectations, increasing the importance of public station attributes such as infrastructure reliability (e.g., consistent service provision, recognizable network providers), access to nearby amenities (e.g., shopping, dining, or recreation), and convenience in terms of trip compatibility and minimal detour requirements. Rather than reducing the need for public investment, widespread private charging access (like at workplaces) may raise user standards for public infrastructure. Planning strategies must anticipate this dynamic by ensuring that public stations offer not merely availability but also context-sensitive experiences to retain relevance for EV users.

Finding 4: *Opportunistic charging behavior alone does not significantly predict public station selection patterns.*

Despite theoretical expectations that flexible, opportunity-driven behaviors might indicate a broader sensitivity to station features, users who reported charging in small amounts whenever the opportunity arises exhibited no significant difference in charging selection profile membership. This suggests that opportunistic micro-behaviors may not necessarily translate into a more nuanced or expanded evaluative framework when selecting public charging stations. From a planning perspective, this highlights that behavioral markers observed at a single point in time may not reliably predict deeper infrastructure engagement patterns. Nevertheless, future research should prioritize collecting dynamic, real-time behavioral data (e.g., charging session logs) or detailed choice experiments to better examine how situational flexibility interacts with long-term station selection strategies.

Finding 5: *EV usage purpose shows a strong influence on charging station preferences, especially for business-related and commuting-related driving.*

Our causal framework further reveals that users who primarily use their EVs for business-related travel are significantly more likely to prioritize features such as reliable station operations (e.g., positive reviews, recommendations by friends and family), compatibility with schedules (e.g., station availability on the way), and situational attributes such as proximity to meeting locations or delivery destinations. This likely reflects the higher operational stakes associated with business travel, where infrastructure failures or unpredictable station performance could lead to missed appointments, delivery delays, or financial penalties. Conversely, users whose primary EV trips are between home and work prioritize the predictability of access (e.g., location area of the station) and minimal disruption to daily routines (e.g., low waiting times), aligning with the efficiency-oriented profile. From a planning standpoint, these findings emphasize the need to differentiate public charging infrastructure offerings based on trip purpose. Infrastructure solutions should recognize that work-oriented users require higher reliability and logistical support, while routine commuters demand consistent access, and leisure users could potentially benefit from co-located amenities that enhance comfort or convenience. Failing to account for these differentiated needs may limit station utility across user segments and undermine infrastructure effectiveness.

Finding 6: *Public charging reliance, not general EV usage intensity, drives more selective station evaluation.*

Compared to users who charge less than once a month, we find that public charging frequency is a strong predictor of profile membership. Users who charge at public stations on a monthly or weekly basis are significantly more likely to belong to the Information-Responsive profile which prioritizes infrastructure reliability, proximity to amenities, situational compatibility, and technical compatibility with their EVs. In contrast, overall EV driving frequency, whether monthly or weekly, shows no statistically significant association with profile membership. This distinction highlights that it is engagement with the public charging network, not merely the frequency of EV usage, that shapes how users evaluate station features. From a planning perspective, these results indicate that users who regularly rely on public infrastructure form expectations around station quality, accessibility, and amenity integration. Infrastructure expansion efforts should prioritize enhancing the reliability, user information systems (e.g., on real-time availability), and co-location of services at high-use sites, ensuring that the needs of frequent public chargers are systematically met. Neglecting this group may risk reinforcing dissatisfaction and limiting the effective utilization of public charging investments.

Finding 7: *Expanding the number of chargers alone will not ensure sustainable utilization or user satisfaction.* First, our factor analysis revealed that EV users evaluate stations based not only on technical attributes like cost and charging speed, but also on experiential needs such as provider reliability, availability of nearby amenities, and compatibility with individual schedules and vehicle characteristics. Second, the segmentation of users into Efficiency-Oriented and Information-Responsive profiles demonstrated that while some users may prioritize availability, a substantial portion demands context-sensitive features beyond physical proximity. Third, our causal analysis showed that users with private chargers (who have alternative options) become more selective about public station quality, and that frequent public charging heightens sensitivity to infrastructure reliability and service integration. Future strategies must therefore integrate behavioral segmentation insights into infrastructure design, ensuring that new stations meet the diverse expectations and usage patterns of EV drivers rather than relying on density alone as a proxy for accessibility.

Our findings emphasize that user preferences are shaped by complex interactions among infrastructural access, behavioral routines, and situational contexts. Effective strategies must recognize heterogeneity in charging motivations, prioritize quality-of-experience features, and integrate infrastructure design with users' broader mobility needs. While our study offers insights into EV charging preferences and adoption expectations, several limitations should be considered. First, due to sample size constraints ($n \approx 300$), we do not model multiple treatments simultaneously within a single causal framework. Although inverse propensity weighting provides unbiased estimates under unconfoundedness, jointly estimating effects for multiple treatments would violate overlap assumptions and lead to unstable balancing weights. Second, while we included key confounders in our models and verified covariate balance post-weighting, unobserved or omitted variables may still bias estimates. For instance, we lacked information on the duration of EV ownership, residential stability, local station density, or commuting regularity, each of which could plausibly influence both treatment and outcome. Finally, all analyses rely on self-reported survey responses, which may be subject to recall bias, social desirability effects, or mismatches between stated and revealed behavior. Future work should expand our framework and allow for interaction effects between treatments and subgroup heterogeneity across sociodemographic strata. Access to detailed large-scale mobility data, real-time charging logs, or usage-based insurance data would also enable validation of the findings and support more robust inferences. In addition, experimental or quasi-experimental designs (e.g., encouragement designs or instrumental variable strategies) could help isolate the behavioral effects of treatment pathways such as test drives or public infrastructure improvements. As EV adoption accelerates, understanding the interplay between structural constraints, experiential learning, and user preferences will be critical to designing sustainable charging ecosystems.

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