TRB Annual Meeting

Understanding the Perception Differences of Charging Infrastructure among Electric Vehicle (EV) and Non-EV Users: a Network Analysis Perspective

--Manuscript Draft--

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Understanding the Perception Differences of Charging Infrastructure among Electric Vehicle (EV) and Non-EV Users: a Network Analysis Perspective

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ABSTRACT

In this study, we raise the concern that current understandings of user perceptions and decision-making processes may jeopardize the sustainable development of charging infrastructure and wider EV adoption. This study addresses three main concerns: (1) most research focuses solely on battery electric vehicle users, neglecting plug-in hybrid (PHEV) and non-EV owners, thus failing to identify common preferences or transitional perceptions that could guide an inclusive development plan; (2) potential factors influencing charging station selection, such as the availability of nearby amenities and the role of information from social circles and user reviews, are often overlooked; and (3) used methods cannot reveal individual items' importance or uncover patterns between them as they often combine or transform the original items. To address these gaps, we conducted a survey experiment among 402 non-EV, PHEV and EV users and applied network analysis to capture their charging station selection decision-making processes. Our findings reveal that non-EV and PHEV users prioritize accessibility, whereas EV owners focus on the number of chargers. Furthermore, certain technical features, such as vehicle-to-grid capabilities, are commonly disregarded, while EV users place significant importance on engaging in amenities while charging. We also report an evolution of preferences, with users shifting their priorities on different types of information as they transition from non-EV and PHEV to EV ownership. Our results highlight the necessity for adaptive infrastructure strategies that consider the evolving preferences of different user groups to foster sustainable and equitable charging infrastructure development and broader adoption of EVs.

Keywords: electric vehicles, public charging infrastructure, user perspectives, EV adoption

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 from 7% to 10% within just one year, from 2022 to 2023. This trend is anticipated to continue, with projections forecasting up to 12.8 million EV sales in the U.S. by 2035. Several factors contribute to this rapid growth, including advancements in battery technologies (*2*), government incentives (*3*), and increased consumer awareness (*4*). At the same time, the expansion of charging infrastructure at both local and national levels has provided essential support for EV users, particularly those without home charging options, facilitating ease of travel within and between areas. This dynamic creates a positive feedback loop where growth in EV adoption and charging station expansion mutually reinforce each other (*5*). Nevertheless, to ensure the sustainable development of charging infrastructure alongside steady growth in EV adoption, a critical question remains: What are the current and potential users' preferences and attitudes guiding their decision in selecting a public charging station?

Answering this question is crucial, as neglecting users' preferences could jeopardize the sustainable growth of EV adoption and the equitable development of charging infrastructure. This could lead to a scenario where the majority of usage is concentrated in a few stations, exacerbating inequities in access. Therefore, understanding the perceptions of both existing EV users and potential adopters is essential to effectively meet the needs of both groups. Additionally, it is important to consider a wide range of factors that might influence the selection of charging stations (*6*). For instance, EV users often engage in other activities while their vehicles are charging due to the longer charging times (*7*). This behavior suggests that the selection of a charging station may be secondary to choosing a primary activity location, such as grocery shopping. Thus, these factors should be included in the analysis of charging perceptions. Additionally, social influence plays a significant role in the decision-making process for purchasing vehicles where knowing more people with EVs increases the likelihood of purchasing one (*8*). This influence may extend to selecting charging stations, where recommendations from friends and family can be impactful, especially for users with little prior charging experience. Finally, a comprehensive modeling approach is needed to uncover the underlying patterns among these factors without relying solely on the modeler's interpretations.

In this study, we conduct an online experiment targeting three user groups: non-EV users, plug-in hybrid electric vehicle (PHEV) owners, and battery electric vehicle (BEV) owners. Respondents are asked to state their preferences regarding charging activities at public charging stations. We further tend to capture their underlying decision processes by evaluating various factors related to perceptions of the charging infrastructure. Additionally, we introduce a network analysis approach to the survey data, addressing limitations in existing methods for analyzing Likert-style surveys while allowing us to reveal the underlying structure of connections between survey items. We specifically aim to explore the following questions:

1. What are the common patterns in the interconnections between infrastructure and user perception features among EV, PHEV, and Non-EV users?
2. How does the opportunity to engage in nearby amenities while charging affect the selection of charging stations for different user groups?

3. What is the role of social influences, such as recommendations from friends and family and user reviews, compared to their own previous satisfaction experiences, in the decision-making process across different user groups?
4. How do preferences evolve from non-EV to PHEV and then to EV users, and what are the implications for infrastructure development strategies?

By answering these questions, we seek to uncover the decision-making patterns of current and potential charging infrastructure users, offering insights to guide the sustainable development of transportation electrification. The rest of this study is organized as follows. First, we provide a background on related studies and the existing gaps in Section 3. We then introduce the survey data for our study, accompanied by the design procedure and descriptive statistics in Section 4. In Section 5, we describe the step-by-step generation of the network from survey items and the analysis of the network. Sections 6 and 7 present the results and main findings. Finally, Section 8 provides conclusions and directions for future work.

BACKGROUND

The adoption of electric vehicles (EVs) remains an essential component of the federal and statewide environmental justice vision and energy resilience. Alongside the national objective of establishing a network of 500,000 public chargers by 2030 (*9*), 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 (*10*). 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 (*11, 12*). Nevertheless, sufficient access to charging infrastructure remains a significant hurdle that must be overcome to drive the uptake of EVs (*5, 13*). Therefore, the equitable 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 (*14, 15*).

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. In this regard, including different groups of vehicle owners is essential, as it allows us to capture the preferences of both current EV users and potential adopters. Studies have indicated that these groups 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 (*16–19*). Additionally, an analysis aiming to identify users' perceptions and preferences should include individual user attitudes, such as range anxiety (*20*), as well as their perceptions or interactions with the actual infrastructure, such as the number of chargers (*21*). In this regard, studies have found factors related to charging infrastructure, such as location (*22*), type of chargers (*23*), energy source (*24*), and charging time (*25*) to be significant in charging station selection. Additionally, certain factors related to user perceptions, such as range anxiety and battery range (*20*), and situational characteristics of charging, such as time of day (*6*), home charging availability (*26*), and detour time (*27*), have also been found influential in users' perception 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. 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 (*26*). Furthermore, another group of features is related to the opportunity to engage in nearby activities, such as dining or shopping, while charging their vehicle. 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 (*28*).

Moreover, 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 (*29*), sensitivity analysis (*30*), or predictive modeling of some variables based on others. To identify the key features that are more important to user groups, analysis often employs principal component analysis (PCA) (*31*). However, PCA has limitations, as it depends heavily on the authors' interpretations of the components and can obscure or remove underlying patterns between the individual items (*32*). Specifically, PCA transforms the original variables into a set of uncorrelated principal components, which can make interpreting these components challenging and potentially mask important relationships between the original variables. To address these shortcomings, a growing body of research focuses on the network properties of surveys. While network modeling has been extensively used in fields such as social network analysis (*33*), biological network analysis (*34*), and association mining of customer preferences (*35*), it has not been widely applied to survey analysis for charging infrastructure preferences. This is primarily due to challenges presented by Likert-style surveys, such as the ordinal nature of the data and the difficulty in defining meaningful edges or connections between survey items. Despite these challenges, network analysis offers a promising alternative, as various network analysis tools can be applied to capture both the individual importance of survey items and the underlying structures of connections between the items.

Based on our literature review, it is evident that understanding users' perceptions and preferences regarding charging infrastructure is critical for achieving zero-emission goals. This exploration must account for different user groups and a wide range of factors that might influence charging station selection, following a methodology that provides a deep understanding of feature importance and the patterns between them. To address these limitations, we design a survey targeting three main user groups: non-EV users, plug-in hybrid electric vehicle (PHEV) users, and battery electric vehicle (BEV) users. Our survey includes questions about users' charging selection and usage pattern characteristics. Specifically, we include survey items related to social influence on the selection of charging stations and preferences for engaging in nearby activity opportunities. We further employ a network analysis approach to the survey, addressing challenges in existing methods for analyzing Likert-style surveys while allowing us to reveal the underlying structure of connections between items.

DATA

Survey Design and Procedure

In this study, we conducted an online experiment to investigate respondents' stated preferences and choice outcomes, aiming to determine the perceived importance of various features related to charging station selection and usage under different hypothetical scenarios. The online survey comprises 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. We mention that only U.S. residents were eligible to complete the survey. The second part of the survey focuses on three main categories of questions: (1) preferences for selecting a public charging station (e.g., *"Which of the following characteristics or features would be important to you when choosing a charging station?"*), (2) participants' charging pattern preferences (e.g., *"I often worry about running out of power when my battery level drops below a certain point"*), and (3) their broader environmental views (e.g., *"Humans have the right to modify the natural environment to suit their needs."*) (*36*). 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 human subjects for research (*37, 38*).

Descriptive Statistics

Participants Background

We collected a total of 432 responses, of which 30 were excluded due to incomplete information. Out of the remaining 402 responses, we report that 149 (37.1%) respondents own gasoline vehicles, 138 (34.3%) own electric vehicles (EVs), and the remaining 115 (28.6%) own plug-in hybrid electric vehicles (PHEVs). The respondents have a median age of 39.0 years, ranging from 19 to 84 years old. Among the respondents, 59.0% are male, and 64.2% reported their race as White, 13.4% as Black, and 15.7% as Asian, while 9.2% identified as Hispanic. Additionally, 46.8% of the respondents have a graduate degree, 29.1% hold a bachelor's degree, 11.9% have an associate/junior college degree, and the remaining have a high school education or less. Employment status indicates that 73.9% work full-time and 12.4% work part-time. In terms of annual income, 44.8% report earning over \$110,000, while 21.6% earn less than \$60,000. Table 1 displays the background information of the three participant groups based on their vehicle ownership. As shown in Table 1, we report that EV owner participants have a 17% higher percentage of males (66.67%) compared to non-EV users (48.99%). In terms of education, EV owners are more likely to have a Bachelor's degree (50.72%) or higher, with 31.16% holding a graduate degree, compared to non-EV users, who have 40.94% and 27.52%, respectively. Regarding employment, a higher percentage of EV owners work full-time (82.61%) compared to PHEV users (73.91%) and non-EV users (65.77%). When examining income, both EV owners and PHEV owners are twice as likely to earn over \$150,000 (24.63% and 24.56%, respectively) compared to non-EV users (11.64%). In terms of race/ethnicity, EV owners are predominantly White (60.14%), though this is lower compared to non-EV users (75.84%) but higher than PHEV users (53.91%). Additionally, EV owners have a higher representation among Black (17.39% vs. 5.37%) and Asian (14.49% vs. 12.08%) respondents compared to non-EV users.

TABLE 1: Description of Demographic Survey Items ($N = 402$)

Category	**Values (%)**	**EV Ownership Status**		
		Non-EV	PHEV	EV
Gender	Female	47.65	36.52	33.33
	Male	48.99	62.61	66.67
	Other	3.36	0.87	0.00
Education	Less than high school	0.67	0.00	0.00
	High School	15.44	10.43	9.42
	Associate/Junior college	15.44	11.30	8.70
	Bachelor's	40.94	49.57	50.72
	Graduate	27.52	28.70	31.16
Employment	Other	8.05	8.70	5.80
	Retired	8.72	4.35	5.07
	Working full-time	65.77	73.91	82.61
	Working part-time	17.45	13.04	6.52
Income	<$25,000	9.59	10.53	5.80
	$25,000-$60,000	29.45	23.68	12.32
	$60,000-$75,000	13.01	11.40	13.04
	$75,000-$110,000	19.86	19.30	31.16
	$110,000-$150,000	16.44	10.53	13.04
	>$150,000	11.64	24.56	24.63
Race/Ethnicity	White	75.84	53.91	60.14
	Black	5.37	14.78	17.39
	Asian	12.08	14.78	14.49
	Hispanic	2.01	9.57	4.35
	Other	4.70	6.96	3.62

Charging Perceptions and Preferences

Our collected data ($N = 402$) on respondents' charging station preferences and selections include their stated preferences, determined using a Likert scale. Participants chose from 1 to 5 to indicate their level of perceived importance of an item (from 1="not at all important" to 5="very important") or from 1 to 7 to indicate their level of agreeableness with an item (from 1="strongly disagree" to 6="strongly agree"). For consistency in our analysis, responses on the 7-point scale were converted to a 5-point scale. Our survey collects a total of 89 questions addressing various groups of factors, such as infrastructure perceptions, charging patterns, and environmental views. However, for this study, we specifically focus on two primary groups of features: preferences related to charging infrastructure (referred to as ‘infrastructure’) and individual perceptions of the charging activity (referred to as ‘perceptions’). Specifically, in these questions we ask respondents, “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?” Respondents then rate their preference on a scale from 1 to 5 regarding their perceived level of importance for each factor. Table 2 shows the survey items related to charging perceptions and preferences, along with their summary statistics across the respondents.

TABLE 2: Description of Preference Survey Items ($N = 402$)

Category	Abbr.	Description	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
	IN1	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.	14.93	19.9	31.34	22.64	11.19
	IN2	Charging network provider: The company or network providing the charging station services.	14.68	21.39	28.61	23.13	12.19
	IN3	Vehicle-to-grid (V2G) capabilities: Whether your electric vehicle can contribute power back to the grid.	25.37	28.11	26.12	13.68	6.72
	IN4	Accessibility of charging station: The overall ease of reaching the charging station.	0.25	1.74	8.21	29.1	60.7
Infrastructure	IN5	Amenities: Access to a restaurant or shopping mall next to the charging station.	4.48	12.94	28.61	32.09	21.89
	IN6	Battery swapping/switching: Whether the charging station offers battery swapping or switching services.	26.87	25.62	24.63	12.44	10.45
	IN7	Location area of charging station: The geographical area where the charging station is located, like residential, work, or commercial locations.	1.99	2.74	14.18	26.37	54.73
	IN8	Available sockets/piles (#): The number of available charging outlets or piles at the charging station.	1.0	2.74	13.93	34.83	47.51
	IN9	Opportunities for other activities during charging: Whether you can engage in other activities, such as shopping or working, while your vehicle is charging.	3.48	9.7	27.86	33.58	25.37
	PE1	Range anxiety: The level of concern or worry you experience about running out of battery power before reaching your destination.	1.74	8.21	16.92	27.86	45.27

Category	Abbr.	Description	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
	PE2	Previous satisfaction: Whether or not you have visited a charging station before and were satisfied with the experience using it.	1.49	4.98	21.39	38.31	33.83
	PE3	Driver risk attitudes: Your personal attitude towards risk and safety while driving an electric vehicle.	6.72	13.68	27.61	29.35	22.64
Perceptions	PE4	Environmental consciousness: Your level of concern and commitment to environmental issues and sustainability.	6.72	16.67	27.36	28.11	21.14
	PE5	Awareness of charging infrastructure: Your level of knowledge and awareness of available charging stations.	1.99	8.96	31.09	30.6	27.36
	PE6	Recommendations by friends and family: Recommendations by friends and family when exploring a new charging station.	12.69	19.9	29.35	26.87	11.19
	PE7	Reviews: Previous user reviews when trying out a new charging station.	2.24	10.7	28.36	33.58	25.12

METHODOLOGY

Our methodology is based on network analysis (NA) to explore the interrelationships among the survey items, where participants express their perceived level of importance for an item on a scale of 1 (“not at all important”) to 5 (“very important”). By treating each survey item as a distinct unit of analysis, we aim to understand the importance of individual items as well as their interconnections based on respondents’ answers. This approach differs from conventional principal component analysis (PCA) or exploratory factor analysis (EFA) by capturing the local connections between individual items (nodes) to reveal features of the overall phenomenon rather than focusing on identifying collective trends and relying heavily on researchers’ interpretation of principal components (*31, 39*). This further allows us to map connections between survey items, identify key items driving these connections, and use various tools to explore the underlying patterns and clusters.

In the following, we detail the primary steps for (1) constructing and (2) analyzing the network of our survey items. Our network generation follows a similar approach to the NALS algorithm introduced by Dalka et al. (*32*), which has been demonstrated to outperform PCA in detailing the underlying network and cluster structures. However, our analysis diverges from the original algorithm, incorporating modifications tailored to our specific hypotheses.

Network Generation

The objective of network generation is to construct a network from the survey responses, where each node represents an individual survey item, and connections between nodes are based on the similarity of collective responses. To this end, we take the following steps.

Bipartite Graph of Survey

Initially, we construct a bipartite graph $B = (U,V,E)$ from the survey data. Here, U represents the set of participants, with each node $u_i \in U$ corresponding to a single participant, and V represents the set of possible responses to the survey items, with each node $v_j \in V$ representing a specific response option (totaling the number of questions $\times$ 5, due to 5 Likert levels). The edge set E consists of edges e_{ij} based on participants' survey responses. In specific, an edge exists between $u_i \in U$ and $v_j \in V$ if participant i selected response j for a given question.

Bipartite Graph Projection

Next, we will project the bipartite graph $B = (U,V,E)$ onto the set of response nodes V. This projection is necessary to analyze the relationships between survey responses directly, as it allows us to focus on the connections among responses rather than between participants and responses. In the projected graph $G = (V,E')$, each node $v_i \in V$ represents a survey response, and an edge $e'_{ij} \in E'$ exists between two nodes v_i and v_j if there is at least one participant who selected both responses i and j. The weight of each edge w_{ij} in the projected graph is defined as the number of participants who selected both responses i and j. Mathematically, this can be expressed as:

$$w_{ij} = \sum_{u_k \in U} \mathbb{I}(u_k, v_i) \cdot \mathbb{I}(u_k, v_j) \tag{1}$$

where $\mathbb{I}(u_k, v_i)$ is an indicator function that equals 1 if participant u_k selected response v_i, and 0 otherwise.

Adjacency Matrix of Survey Items

To analyze the connections between survey items rather than individual response options, we first construct an adjacency matrix for the projected graph. Each element a_{ij} in this matrix represents the number of respondents who selected both responses i and j. We split this matrix into submatrices A_{pq} for each unique pair of survey items p and q, where the rows and columns correspond to the response options (1 to 5) for each item. We then calculate a single weight w_{pq} representing the connection between survey items p and q, expressed as below:

$$S_{\text{sim}} = \sum_{i=1}^{2} \sum_{j=1}^{2} A_{pq}[i,j] + \sum_{i=4}^{5} \sum_{j=4}^{5} A_{pq}[i,j] \tag{2}$$

$$S_{\text{dis}} = \sum_{i=1}^{2} \sum_{j=4}^{5} (A_{pq}[i,j] + A_{pq}[j,i]) \tag{3}$$

$$w_{pq} = S_{\text{sim}} - S_{\text{dis}} \tag{4}$$

where S_{sim} represents the sum of elements indicating similar responses (e.g., both "important" and "very important"), and S_{dis} represents the sum of elements indicating dissimilar responses (e.g., "not important" and "very important"). Elements corresponding to neutral responses (value of 3) are excluded from this calculation. A positive w_{pq} indicates similar responses, a negative w_{pq} indicates dissimilar responses and $w_{pq} = 0$ indicates no edge between the two items. Following this, we can use the edge weight in the full survey item network to represent the similarity of item selections. However, the edge weight alone does not indicate the level of importance, i.e., whether two survey items are connected through mutual selections of low or high levels of importance.

Therefore, we include an additional edge attribute, "temperature", which captures the difference between the number of high importance and the number of low importance selections for each pair of survey items. Specifically, temperature is calculated as:

$$T_{pq} = \sum_{i=4}^{5}\sum_{j=4}^{5} A_{pq}[i,j] - \sum_{i=1}^{2}\sum_{j=1}^{2} A_{pq}[i,j] \quad (5)$$

where T_{pq} is continuous, ranging from $-N$ to $+N$, with N being the total number of participants. An edge with a negative temperature indicates that the two items are often both perceived as not important, while a positive temperature indicates that the two items are often both selected as important.

Backbone Network

The graph obtained in the previous step may include connections formed by only one or two participants, which can introduce noise and make the network extremely dense. To ensure the graph accurately reflects meaningful connections, we apply a network sparsification technique to identify its backbone, named the Locally Adaptive Network Sparsification (LANS) algorithm (*40*). The algorithm has been effectively used in similar survey data studies (*32, 41*) and operates by comparing the links of each node locally, retaining only those links whose weights are above a certain threshold relative to other links from the same node. For instance, with an α level of 0.05, a link is preserved if its weight is greater than or equal to 95% of the other link weights from that node. Here, by using the absolute value of the edge weights, we retain all links identified as significant at $\alpha = 0.05$ level for at least one node to ensure the network remains connected. Finally, The resulting backbone network of survey items serves as the foundation for subsequent analysis.

Network Analysis

In this section, we conduct an in-depth analysis of the backbone network identified in the previous section. Our primary objectives are twofold: (1) to identify the key characteristics and influential nodes within the network and (2) to understand the underlying structure of the connections between items. To achieve the first objective, we utilize degree centrality and PageRank measures to assess the importance of individual survey items (nodes) within the network. For the second objective, we conduct a Clique Census (CC) analysis, which uncovers tightly-knit groups of items and the modular structure of the backbone network.

Degree Centrality

Our first measure of analysis is degree centrality, a fundamental metric in network analysis that represents the number of direct connections (edges) a node has (*42*). Degree centrality provides a straightforward understanding of a node's immediate influence within the network. By identifying nodes with a high degree of centrality, we aim to pinpoint survey items perceived as significant by a large portion of respondents, highlighting their direct importance. Here, degree centrality values are normalized by the maximum possible degree in a simple graph, which is $N-1$, where N is the number of nodes in G. For a node v_i in the backbone graph $G = (V, E)$, the degree centrality

$C_D(v_i)$ is given by:

$$C_D(v_i) = \frac{\sum_{v_j \in V} a_{ij}}{N-1}, \quad \forall v_i \in V \tag{6}$$

where a_{ij} is an element of the adjacency matrix A, indicating the presence of an edge between nodes $v_i \in V$ and $v_j \in V$.

PageRank

Our second measure of network analysis is PageRank, which measures the importance of nodes based on the idea that connections from highly connected nodes contribute more to a node's importance (*43*). PageRank accounts for both the quantity and quality of connections, emphasizing nodes that are connected to other important nodes. This measure allows us to identify survey items that are central not only due to their direct connections but also due to their association with other influential items, uncovering items that might not have the highest degree but are embedded within crucial network structures. The PageRank centrality $PR(v_i)$ of a node v_i is defined recursively as:

$$PR(v_i) = \frac{1-d}{N} + d \sum_{v_j \in \text{neighbors}(v_i)} \frac{PR(v_j)}{k_j} \tag{7}$$

where d is the damping factor (set to 0.85), N is the total number of nodes, and k_j is the degree of node V_j. the first part of Equation 7 distributes a baseline importance level for all nodes, while the second term distributes importance based on each node's connections.

Overlapping Community Detection

In addition to the importance of individual items in our survey, we are interested in finding underlying patterns in the structure of the network. To this end, we use a clique-based approach to detect tightly-knit groups of survey items, indicating sets of items that are frequently perceived together as important. A clique is a subset of nodes in a graph where every node is directly connected to every other node in the subset. In other words, a k-clique in a graph $G = (V,E)$ is a subset $C \subseteq V$ of size k such that for every pair of nodes $v_i, v_j \in C$, there exists an edge $(v_i, v_j) \in E$. Furthermore, we use the k-clique community measure, which identifies all k-cliques that can be reached through a series of adjacent k-cliques. Two k-cliques are considered adjacent if they share $k-1$ nodes (*44*). The advantage of identifying k-clique communities, rather than focusing on individual cliques, is its applicability to larger networks, which can uncover less obvious groupings between the items. This method has been widely applied in various fields, from analyzing social networks (*45*) to studying biological processes (*46*).

RESULTS

After the projection of the bipartite graph, a network containing 89 nodes and 3916 edges is produced. Then, the projected bipartite graph is converted to a backbone network of survey questionnaire items reflecting only significant interconnections. Since we are mainly focused on understanding the relationship between user perceptions and infrastructure-related features impacting the decision for choosing EV charging stations, sub-graphs of the backbone containing only the infrastructure and user perception-related questionnaire survey items (16 nodes) are created for different user groups, i.e., EV, PHEV, and Non-EV users. The backbone graphs corresponding to EV, PHEV, and non-EV users returned 426, 435, and 458 edges, respectively.

The interconnections between infrastructure and user perception feature for EV users are illustrated in Figure 1. From this figure, we observe that only IN1, IN3, IN6, and PE6 features exhibit mutual disagreement among respondents (blue edges), while the other features share mutual agreement (red edges). This suggests that if EV users do not value V2G capabilities as important, they are also likely to disregard the power station's energy source, battery swapping/switching, and family and friend recommendations when selecting a charging station. In terms of mutual agreement, IN8 (Available chargers) has the highest degree centrality and is connected with IN2, IN4, IN5, IN7, IN9, PE1, and PE7. Thus, EV users who prioritize the number of chargers when selecting a station also place high importance on the charging provider, accessibility of the charging station, amenities nearby, land-use type of the charging station area, and opportunities for other activities during charging. Similar connections exist with IN4 (accessibility of charging station), except for the absence of connections with IN2 (charging station provider) and IN5 (amenities). Additionally, we report other connections between the survey items where PE7 (reviews) is connected to IN2, IN4, and IN8, indicating that EV users who value previous reviews of a charging station also consider its charging network provider, accessibility, and the number of available chargers in their decision-making process.

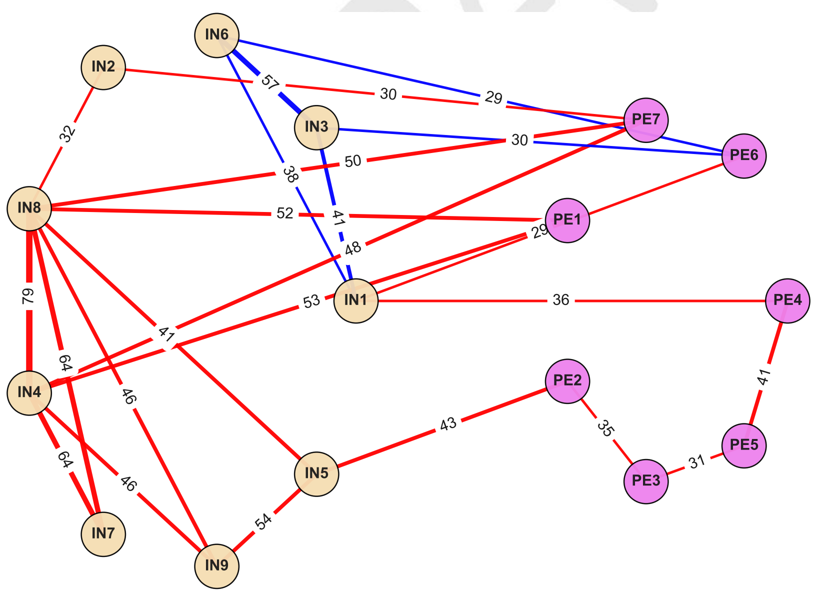

FIGURE 1: Inter-connections between Infrastructure and User Perception related features for EV users. Red and blue connections represent mutual agreement and disagreement respectively. Values on the links, and the link weights reflect the percentage of responses.

Figure 2 reveals the relationships between infrastructure and user perception features for PHEV users. The analysis shows that only the features IN1, IN2, IN3, and IN6 exhibit mutual disagreement among respondents, while the other features share mutual agreement. This suggests that if PHEV users do not consider the charging network provider important, they are also likely to disregard the importance of the energy source of the power station, battery swapping/switching, and V2G capabilities when selecting a charging station. Analyzing the mutual agreements, IN4 (accessibility of charging station) has the highest degree centrality and is connected with IN7, IN8, PE1, PE2, PE5, and PE7. Thus, PHEV users who prioritize ease of access to the charging station also consider land use, available chargers, range anxiety, their previous experience, and other users' reviews important when choosing a charging station. Additionally, PE4 (environmental consciousness) shares connections with PE2, PE3, PE5, PE7, and IN1. Hence, PHEV users who value environmental consciousness also consider previous satisfaction, their risk attitudes, awareness of charging infrastructure, and other users' reviews to be important factors in their decision-making process.

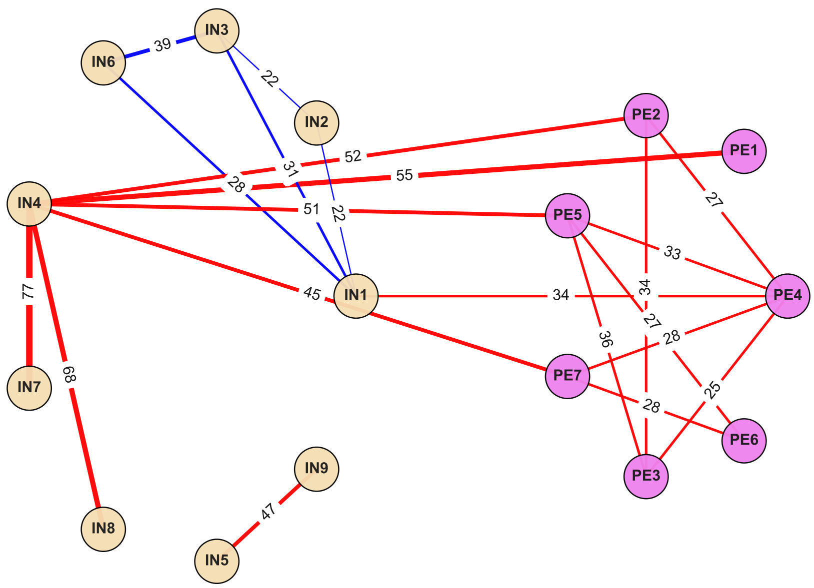

FIGURE 2: Inter-connections between Infrastructure and User Perception related features for PHEV users. Red and blue connections represent mutual agreement and disagreement respectively. Values on the links, and the link weights reflect the percentage of responses.

Figure 3 demonstrates the relationships between infrastructure and perception features for Non-EV users. The analysis indicates that, similar to PHEV users, only IN1, IN2, IN3, and IN6 show disagreement among respondents, while the other connections are in mutual agreement. This finding implies that if non-EV users do not regard the charging network provider as important, they are also likely to overlook the importance of the power station's energy source, battery swapping/switching, and V2G capabilities when choosing a charging station. Focusing on the features with mutual agreement, IN4 (accessibility of charging station) stands out with the highest degree centrality and is linked to IN2, IN7, IN8, PE1, PE2, PE3, and PE5. Consequently, non-EV users who prioritize the overall ease of access to charging stations also consider the charging network provider, location area, and available chargers at the station, as well as range anxiety, previous satisfaction, risk attitudes, and awareness of charging infrastructure to be crucial when selecting a charging location. Furthermore, PE4 (environmental consciousness) is connected with PE2, PE3, and IN1; therefore, non-EV users who prioritize environmental consciousness also place importance on previous satisfaction, driver risk attitudes, and the energy source of the power station in their decision-making process.

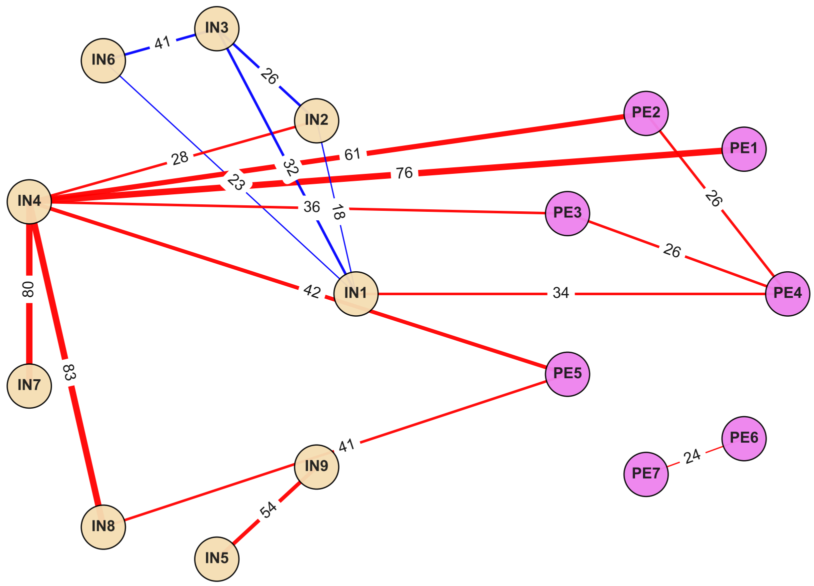

FIGURE 3: Inter-connections between Infrastructure and User Perception related features for Non-EV users. Red and blue connections represent mutual agreement and disagreement respectively. Values on the links, and the link weights reflect the percentage of responses.

Following the results presented, which indicate the importance of individual items based on the significance of response similarity and their mutual agreement or disagreement status, we also seek to examine the relative ranking of nodes in terms of the similarity strength of items. This examination takes into account both the number and quality of their connections among users. To this end, we calculated the PageRank centrality scores for infrastructure and user perception-related features across different user groups. Figure 4 illustrates the changes in ranking these features based on PageRank centrality across various user groups. The figure reveals significant variations in ranking different features among the user groups. For instance, IN8, representing the number of available chargers, is the top-ranked feature among EV users, while both PHEV and non-EV users place the highest rank on IN4, which pertains to the accessibility of the charging station. Among the other top five ranked features for EV users are IN1, IN3, IN4, and IN5, indicating their prioritization of the energy source of the power station, V2G capabilities, accessibility of the charging station, and nearby amenities. For PHEV users, the top five features include IN1, IN3, IN4, PE4, and PE5, reflecting their emphasis on the energy source of the charging power, V2G capabilities, accessibility of charging stations, environmental consciousness, and awareness of charging infrastructure. In contrast, non-EV users rank IN1, IN3, IN4, PE6, and PE7 in their top five, highlighting their focus on the energy source of the power station, V2G capabilities, accessibility of charging stations, recommendations by friends and family, and reviews from other users.

The results shown in Figure 4 further reveal that EV users assign the lowest ranks to IN2, IN7, PE1, PE2, and PE3, which correspond to the charging network provider, the land-use type of the charging station area, range anxiety, previous satisfaction, and driver risk attitudes. For PHEV users, the least prioritized features are IN2, IN7, IN8, PE1, and PE6, indicating that they do not significantly value the charging network provider, the land-use type of the charging station area, number of available chargers, range anxiety, and recommendations by friends and family when making a decision. Conversely, non-EV users place the lowest ranks on IN2, IN7, PE1, PE3, and PE5, demonstrating that the charging network provider, the land-use type of the charging station area, range anxiety, driver risk attitudes, and awareness of charging infrastructure are less critical to the decision process of individuals who do not use EVs.

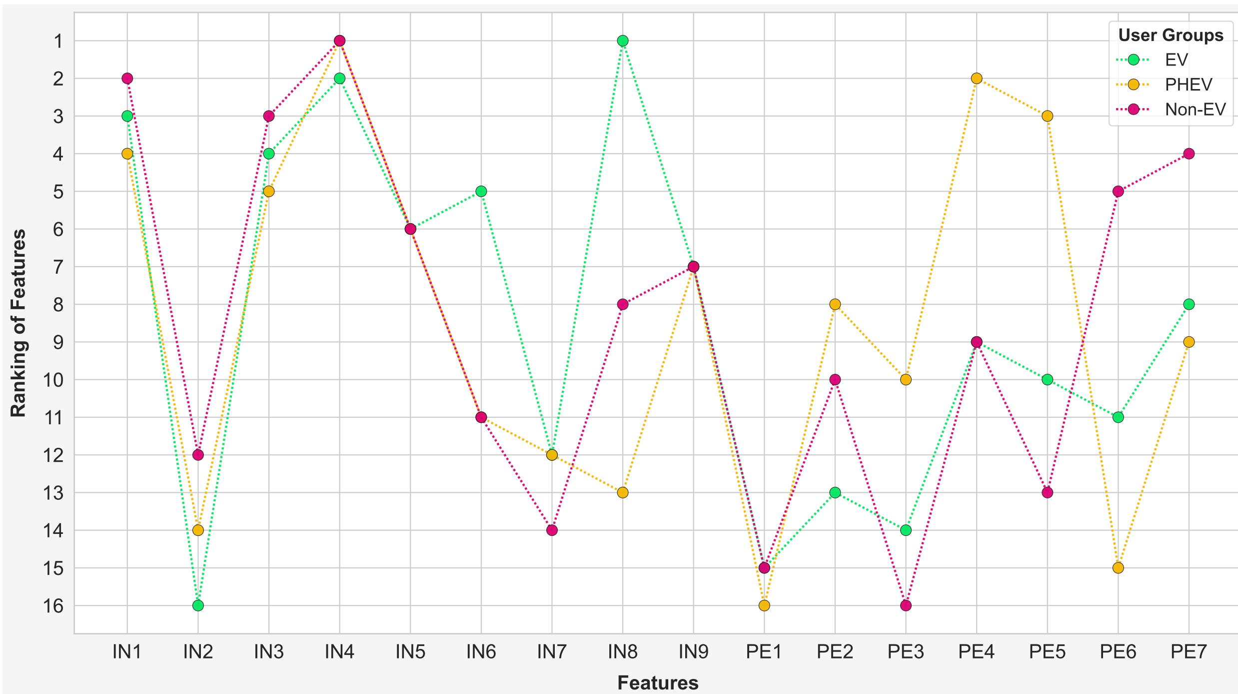

FIGURE 4: Changes in ranking features based on PageRank centrality across different user groups.

Additionally, k-clique community detection analysis was used to identify specific combinations of features that respondents frequently consider together within a sub-network. Here, k=3 is used since the lesser value would yield pairwise relations which can be easily observed from the network structure itself. The community detection analysis revealed two distinct cliques for each network, corresponding to different user groups, as illustrated in Figure 5. Upon assessing these cliques, it is evident that IN1, IN2, IN3, and IN6 form a common clique for both PHEV and non-EV users, while EV users substitute IN2 with PE6. This suggests that PHEV and non-EV users assign similar importance to features such as the charging network provider, the energy source of the power station, battery swapping/switching capabilities, and V2G capabilities. In contrast, EV users place less emphasis on the energy source of the charging network provider and more on other users' reviews of the station, possibly due to their more extensive experience with these stations, as evidenced in the literature (*47*). Furthermore, the second clique for EV users highlights a well-connected sub-network of eight components: charging network provider, accessibility, amenities, number of available chargers, location area of the charging station, opportunities for other activities, range anxiety, and reviews of charging infrastructure. This indicates that EV users collectively value these factors in their charging station experiences. Similar findings have been reported in (*48–52*). In contrast, PHEV users' second clique reveals a network of four user perception-related features, emphasizing their focus on previous satisfaction, environmental consciousness, driver risk attitudes, and awareness of charging infrastructure. This suggests that PHEV users are particularly influenced by these factors in their charging station choices. Non-EV users' second clique includes the number of chargers, accessibility of the charging station, and awareness of charging infrastructure. Overall, these findings underscore different user groups' varying priorities and experiences when selecting and utilizing charging stations, highlighting the nuanced needs and preferences within each category.

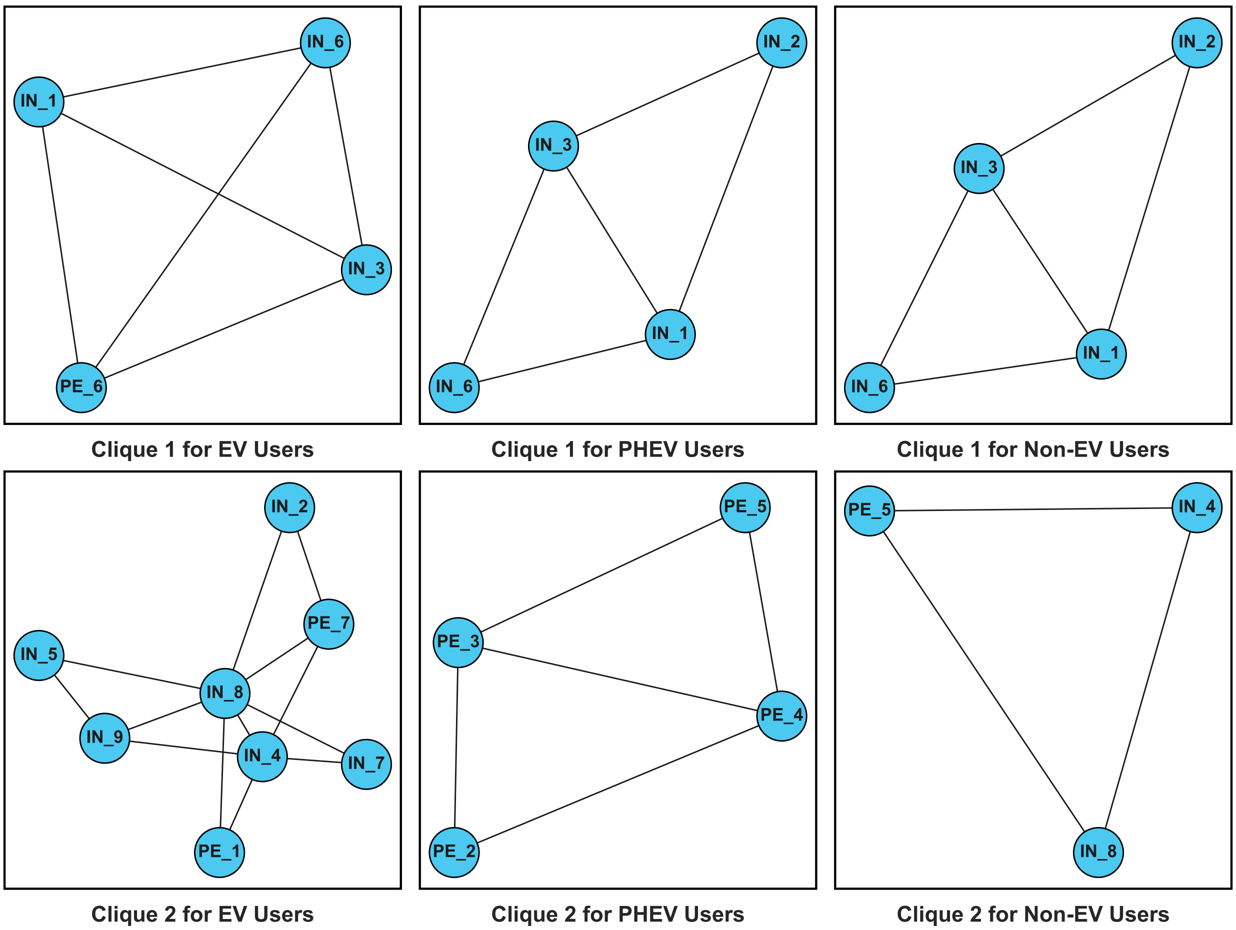

FIGURE 5: Cliques (i.e., sub-networks) connected to prominent features for EV, PHEV, and Non-EV users.

DISCUSSION

This study seeks to understand how user perceptions and infrastructure-related features influence the decision to choose EV charging stations across different user groups: EV, PHEV, and non-EV users. We approached this by analyzing backbone networks derived from bipartite graphs that included questionnaire survey items and their corresponding responses. The backbone networks for EV, PHEV, and non-EV users revealed 426, 435, and 458 edges, respectively, showing a slight increase in interconnections from EV to non-EV users. By employing a network analysis approach, we were able to identify the importance of individual items in the decision-making process while also uncovering the underlying patterns and connections between various items. At the same time, we retained detailed item-level information, avoiding the loss of nuance that can occur when questions are combined or transformed (e.g., into principal components).

In our results, we observe that while mutual agreement features varied notably across user groups, IN4 (accessibility of charging station) emerged as the most connected node for PHEV and non-EV users and the second most connected node for EV users (following the number of chargers). This indicates a shared priority among these groups for the ease of access to charging infrastructure. A similar trend can be observed in Figure 4, which shows the strength of similarities in prioritizing this feature. Nevertheless, EV users tend to prioritize the number of chargers over overall accessibility. This preference can be attributed to their higher baseline level of accessibility during their daily routines, where chargers are more likely to be available at activity locations, work, or home. Additionally, EV users may associate the number of chargers with reduced waiting times and a more seamless charging experience.

Finding 1: *Non-EV and PHEV users commonly perceive ease of access to charging stations as the most crucial infrastructure feature, whereas EV owners place higher importance on the number of available chargers.*

Three infrastructure-related features, namely IN1 (energy source of the power stations), IN3 (V2G capabilities), and IN6 (battery swapping/switching options), consistently exhibited mutual disagreement across all user groups. This indicates that users, regardless of their EV ownership status, generally tend to disregard the importance of these features when selecting a public charging station. This is further evidenced by the high PageRank values of these features, showing a high similarity in the selection of these items in Figure 4, as well as in the clique detection across all groups in Figure 5, highlighting a pattern of disregard for these factors. This consistent trend underscores a broader consensus on the lesser importance of these features in the decision-making process for choosing a charging station.

Finding 2: *Users, irrespective of their EV ownership status, tend to mutually disregard certain factors related to charging infrastructure, such as the energy source of the power stations, V2G capabilities, and battery swapping/switching options when selecting a public charging station.*

Our findings also reveal that IN5 (opportunity to engage in nearby amenities such as dining or shopping) and IN9 (location area of the charging station) significantly influence the decision-making process of EV users. These features are connected to two primary aspects: accessibility (IN4) and the number of chargers (IN8), reflecting mutual agreement. Additionally, they are directly linked to PE2 (previous satisfaction with the charging station), suggesting that users' satisfaction with charging stations is closely tied to their ability to engage in nearby activities. The second clique for EV users further underscores the importance of IN5 and IN9, as they are connected to six other survey items. Conversely, these patterns are not observed among non-EV and PHEV users. This difference likely stems from EV users' experiences at charging stations, where preferences for engaging in activities during charging periods develop, unlike those without EVs who may not have first-hand experiences of waiting times. This can also be regarded as a sign of the evolving preferences of EV users, shaped by their practical experiences and the need to optimize waiting times during charging sessions.

Finding 3: *The opportunity to engage in amenities while charging significantly influences EV users' selection of charging stations, a factor that is notably less important to non-EV and PHEV users.*

Additionally, we examined the role of social influence on charging station selection, focusing on feature PE6 (recommendations from family and friends), and compared it with PE2 (own satisfaction experience) and PE7 (other users' reviews). This comparison helps to identify the relative importance of others' opinions versus personal experiences when choosing a charging station. We found that EV users are likely to dismiss recommendations from family and friends (PE6) if they do not consider the technical features of the station, such as V2G capabilities and battery swapping, important. However, if they are concerned about their vehicle's driving range, they tend to place more weight on recommendations from family and friends. Non-EV users do not connect recommendations from family and friends or reviews from other users with any other features, indicating that they do not consider these recommendations in conjunction with other factors. For PHEV users, recommendations from friends and family align with awareness of charging infrastructure, suggesting that these recommendations are significant when users believe it is crucial to understand the infrastructure. Moreover, reviews become important for PHEV users who prioritize environmental consciousness. We state that this potentially highlights the evolving nature of trust and reliance on social feedback within different stages of EV adoption and usage.

Finding 4: *The influence of reviews and social circles varies across user groups. Non-EV and PHEV users rely more on their own satisfaction experiences and less on other users' reviews, whereas EV users place a greater emphasis on reviews.*

Finally, these findings suggest an evolution of preferences as users transition from non-EV to PHEV and then to EV ownership. Such shift in transitions underscores the dynamic nature of user preferences, highlighting the need for adaptive strategies in developing and expanding charging infrastructure to meet the changing needs of different user groups.

Finding 5: *There is an evolution of preference from non-EV to PHEV and then to EV users, characterized by a shift in prioritizing accessibility, relying less on social circle information, and developing a preferential attachment to nearby amenities.*

Our findings can guide the development of more targeted infrastructure improvements and policies to cater to the specific needs of each user group, ultimately facilitating broader adoption and satisfaction with EV charging solutions. In this regard, our study can generate multiple policy suggestions based on targeting different user groups for the sustainable development of the charging infrastructure. Specifically, for non-EV and PHEV users, enhancing the overall accessibility of charging stations should be a priority, with a strategic focus on placing stations in easily accessible locations such as main roads, retail centers, and community hubs. Public awareness campaigns highlighting the availability and benefits of charging infrastructure can also drive adoption among these groups. For EV users, as well as other groups, adding charging opportunities to frequently visited activity locations, such as workplaces, shopping centers, and recreational areas, can enhance convenience and utilization. To this end, financial incentives for businesses and brands to host charging stations, partnerships with local governments to increase community engagement and feedback mechanisms can also help address the diverse needs of different user groups. Additionally, reliable information tools that provide real-time data on charger availability, types of chargers, and nearby amenities, along with user reviews and satisfaction ratings, can empower EV users to make informed decisions and enhance their overall charging experience.

CONCLUSION

In this study, we aimed to understand how user perceptions and infrastructure-related features influence the decision to choose EV charging stations across different user groups: non-EV, PHEV and EV users. Through a detailed survey and network analysis, we uncovered distinct preferences and priorities among these groups. Non-EV and PHEV users emphasize accessibility, while EV owners focus on the number of chargers. Across all groups, we found a general disregard for the energy source of power stations, V2G capabilities, and battery swapping options. EV users uniquely value the opportunity to engage in amenities while charging. Additionally, the importance of reviews and social circles differs, with EV users placing more weight on reviews. We further report an evolution in preferences from non-EV to PHEV to EV users, underscoring the need for adaptive strategies in charging infrastructure development. These findings offers actionable insights to guide targeted infrastructure improvements and policies, promoting sustainable development that addresses the diverse needs of all user groups.

For future work, we plan to delve deeper into analyzing our survey by incorporating relationships between additional factors related to cost (e.g., charging costs), situation (such as time of day), and participants' broader environmental views. Additionally, the network analysis conducted in our study offers the potential for more comprehensive analyses to use more advanced tools to uncover associations between the items and achieve deeper insights into these processes. Furthermore, we aim to design a more detailed experiment that mimics the actual decision-making process of users through existing routing applications. This will enable us to directly analyze the steps users take to process information across different features, providing a more detailed understanding of their decision-making process.

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