



# Investigating Predictive Models for Electric Vehicle Charging Station Occupancy: A User-Focused Approach

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## ABSTRACT

Predictive models for electric vehicle charging station (EVCS) occupancy hold great promises for addressing issues such as queuing, range anxiety, and ineffective charging practices. Yet the success of these models relies not only on technical accuracy, but also on how well the forecasts align with user expectations and facilitate trust. This paper explores two core questions: (1) What display expectations do EV owners prefer to see for EVCS occupancy prediction? and (2) What are the key factors that influence EV owners' trust in predictive models as a source to manage their charging times? By integrating findings from quantitative surveys (n=191) and qualitative interviews (n=11), this study reveals a general preference for clear, user-friendly prediction displays (particularly bar charts or line graphs) and underscores the importance of contextual clarity (e.g. charging speed, real-time updates) to bolster trust. While novice owners value additional guidance, even experienced users benefit from predictive outputs tailored to specific needs. Our findings suggest that combining simplicity with transparency is pivotal in shaping EV owners' acceptance and reliance on predictive tools.

**Keywords:** Electric Vehicle (EVs), Charging Station Occupancy, Occupancy Forecasting, User Behaviour, Predictive Models, Display Formats.

## 1. Introduction

As electric vehicles (EVs) become increasingly mainstream, public and private stakeholders are striving to ensure the availability of charging infrastructure keeps pace. A growing body of research examines how predictive models can forecast occupancy at EV charging stations (EVCS), aiming to inform drivers about real-time and future charging availability. However, certain barriers remain as users often have diverse expectations of how predictions should be displayed, and differing levels of trust in the reliability of these tools.

This study addresses two central questions:

1. What display expectations do EV owners prefer to see for EVCS occupancy prediction?
2. What are the key factors that influence EV owners' trust in predictive models as a source to manage their charging times?

Mark Dunlop Computer and Information Sciences the University of Strathclyde Glasgow Answering these questions have practical implications for designing effective, user-centric platforms that help EV drivers make informed charging decisions.

## 2. Literature Review

### 2.1. The Role of User Behaviour in Forecasting Charging

Demand A growing consensus supports the importance of user-related variables such as charging habits, preferred locations, and session frequency in predicting demands for EV charging (Majidpour et al. 2016; Nespoli et al. 2023). Integrating these behavioural patterns not only refines the forecasting models but also helps capture the nuanced ways in which EV drivers actually use the infrastructure.

### 2.2. Instrumental Factors in EV Charging Behaviour

The literature highlights several influences on EV charging behaviour:

1. Charging Mode and Speed: The availability of fast chargers can substantially alter user charging patterns (Velychko et al. 2022). Rapid chargers often appeal to those looking for quick top-ups or travelling longer distances.
2. Location and Convenience: Many studies confirm that home charging is dominant due to ease of access and potential cost advantages (Anderson et al. 2023; Morrissey et al. 2016). Workplace and public chargers, in turn, come to the fore for daytime top-ups,

particularly during peak usage hours or longer trips (Morstyn et al. 2018). Public stations, however, are vital for longer trips and for EV owners without domestic chargers.

3. User Education and Awareness: Knowledge gaps surrounding charging technologies can hinder EV adoption and frustrate more flexible charging solutions (Anderson et al. 2023). Many users report that public charging remains insufficiently developed in certain regions, limiting opportunities for flexible travel and unplanned stops (Morrissey et al. 2016). Also, user's personal circumstances, such as driving style or comfort with technology, can affect choices 2) Analysis about when and where to charge (Xing et al. 2020; Anderson et al. 2023).
4. Sustainability and Grid Implications: Charging often overlaps with peak electricity demand, prompting proposals to align EV charging with off-peak hours or renewable energy sources to enhance sustainability (Lavrenova and Denysiuk 2023).

### 2.3. Integrating Stakeholder Perspectives

A recurring limitation in many predictive models is the lack of input from EV owners themselves (Douaidi et al. 2023). Despite widespread recognition of privacy concerns with advanced analytics like federated learning, the more practical question of how EV owners perceive, trust, and intend to use these predictive models often remains unexplored. A user-oriented approach, incorporating feedback on display formats and interpretability, enhances the likelihood that predictive tools will be adopted in everyday practice. Whilst model accuracy is vital, several authors have noted a relative dearth of user-focused evaluations of these predictive tools (Douaidi et al. 2023). Incorporating stakeholders' insights (particularly EV owners) into the development process is crucial for designing intuitive displays, building trust, and encouraging widespread adoption.

## 3. Methodology

This study employed a mixed-methods approach, with separate quantitative and qualitative phases to explore and validate the research questions from complementary angles.

### 3.1. Quantitative Survey

A quantitative survey was administered online to EV owners to capture broad trends in charging habits, battery management, and display preferences for EVCS occupancy predictions.

- Demographics and Operational Information: Included participants' age, gender, and EV ownership duration.
- Charging Habits: Explored preferences for location, charging modes, and typical times of day.
- Prediction Display Usability: Presented multiple display formats of predictive outputs, ranging from graphical

(bar charts, line graphs) to textual short descriptions. 1) Data Collection

- Platform: Qualtrics
- Sampling: Targeted adverts were posted on Facebook and X (formerly Twitter) EV groups to recruit participants with EV ownership experience
- Ethical Approval: Granted by the University of Strathclyde Departmental Ethics Committee (Approval Number: 2018).
- Response Rate: Over 200 volunteers; 191 valid responses were retained after excluding incomplete surveys. Survey data were analysed with IBM SPSS Statistics (v.29.0.2.0).

Descriptive statistics and inferential tests (e.g., chi-square for associations between preferred charging time and location) examined behavioural patterns. Likert-scale responses on preferred display modes were also interpreted with standard interval scaling to categorise attitudes from “dislike a great deal” to “like a great deal.”

### 3.2. Qualitative Interviews

To further investigate the role of trust and preferences for predictive displays, semi-structured interviews were conducted with 11 EV owners in the UK. The interviews focused on:

- Charging Accessibility and Perceptions: Use of online platforms, experiences during longer journeys.
- Testing Model Display Modes: Participants were shown scenarios illustrating occupancy predictions in varying formats (graphical, text, and categorical).
- Trust in Model Predictions: Participants were asked to compare predicted vs. actual occupancy in real data scenarios, assessing whether discrepancies undermined their confidence.

#### 3.2.1. Interview Procedure

- Structure: Three sections demographic details, (2) perceptions on charging accessibility, and (3) evaluating model usability and trust.
- Recruitment: E-advertisements in EV communities. Despite initial interest from 15 individuals, 11 took part in full interviews.
- Ethical Approval: Granted by the Departmental Ethics Committee (Approval Number: 2205).

#### 3.2.2. Qualitative Data Analysis

Interview recordings were transcribed and subjected to a six phase thematic analysis (Braun and Clarke 2006). Codes such as “trust in predictions,” “graphical preference,” and “accuracy concerns” were collated into broader themes (e.g., “Conditional Trust in Predictive Models”). This thematic approach uncovered patterns in user attitudes towards predictive tools and display formats.

## 4. Results

### 4.1. Quantitative Survey Findings

#### 4.1.1. Participant Demographics

Of the 191 valid survey participants, roughly half were in the 26–35 age range. Whilst women comprised a slight majority overall, the 26–35 group had more male participants than other age brackets. Ownership duration was typically longer than one year, suggesting a fairly seasoned group of EV drivers.

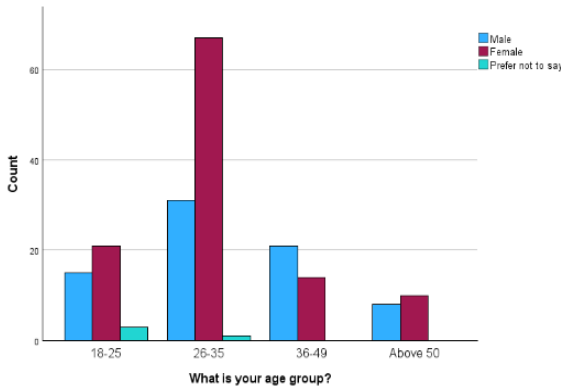


Fig. 1. Gender Representation Across Age Groups

#### 4.1.2. Charging Behaviour

##### A. Preferred Charging Location:

Home charging dominated (over half the sample), consistent with Anderson et al. (2023). The rest primarily used workplace or public chargers.

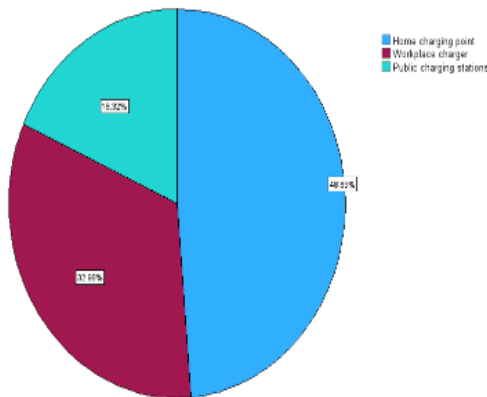


Fig. 2. Preferred Charging Location

##### B. Time of Day:

Most participants favoured mid-day or overnight sessions. A chi-square test ( $p < 0.05$ ) showed a significant association between charging time and location, reflecting that overnight charging was especially popular at home, whilst midday sessions were more common at workplace chargers.

**Table 1.** (a) Relationship Between Preferred Charging Locations for EVs and Preferred Time of Day: Chi-square Test Results, (b) Symmetric Measures Analysis

#### Chi-Square Tests

|                              | Value                | df | Asymptotic Significance (2-sided) |
|------------------------------|----------------------|----|-----------------------------------|
| Pearson Chi-Square           | 105.516 <sup>a</sup> | 4  | <.001                             |
| Likelihood Ratio             | 121.593              | 4  | <.001                             |
| Linear-by-Linear Association | 44.320               | 1  | <.001                             |
| N of Valid Cases             | 191                  |    |                                   |

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 5.86.

#### Symmetric Measures

|                        | Value | Approximate Significance |
|------------------------|-------|--------------------------|
| Nominal by Nominal Phi | .743  | <.001                    |
| Cramer's V             | .526  | <.001                    |
| N of Valid Cases       | 191   |                          |

#### 4.1.3. Battery Depletion Risk

Many participants had experienced being close to running out of battery at least once. Newer EV owners (less than one year of experience) reported greater anxiety about reaching a charger with minimal charge remaining, suggesting that familiarity with range limitations mitigates these concerns over time.

#### 4.1.4. Preferences for Online Platforms and Display Modes

Most participants felt comfortable using online tools to estimate occupancy. Additionally, short-term predictions (less than six hours ahead) were strongly preferred to extended forecasts.

Regarding the display of predictive results:

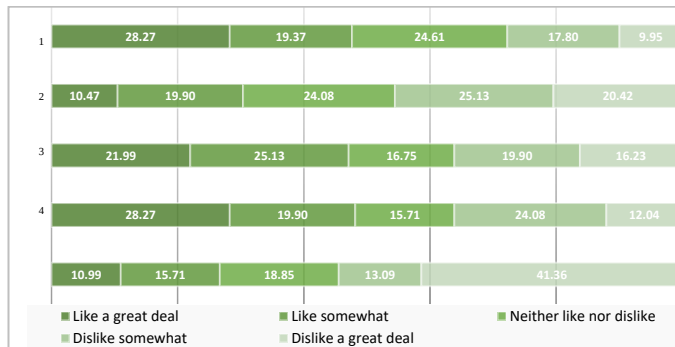
- Bar Charts, Density and Line Graphs were rated highly for clarity.
- Textual Displays also attracted moderate favour but could become confusing for rapidly changing predictions.
- Categorical Levels (e.g. “Moderately Full”) were generally less appealing due to perceived vagueness.

These findings reinforce the importance of clear, easily digestible visual outputs when conveying occupancy predictions to EV drivers.

## 4.2. Qualitative Interview Insights

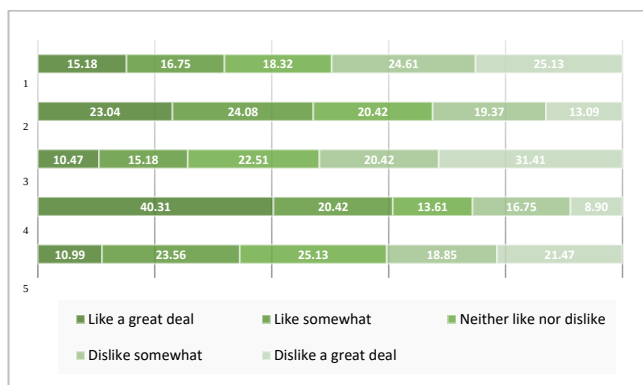
This section presents the thematic analysis of the data arising from interviews conducted with the 11 EV owners, aiming to explore users' beliefs concerning predictive models for EVCS occupancy, focusing on themes related to trust, data display, and the challenges associated with predictive accuracy. The thematic analysis followed the six-phase approach of Braun and Clarke (2006), ensuring a rigorous and systematic examination of the data.

1: Density-plot. 2: Dot-plot. 3: Textual display. 4: Line-graph. 5: Marginal-plot



**Fig. 3.** Participants' Rating Distribution for Display Models-Group1

1: Scatterplot. 2: Textual display. 3: Marginal-plot 4: Bar-chart. 5: Pie-chart



**Fig. 4.** Participants' Rating Distribution for Display Models-Group2

#### 4.2.1. Familiarizing with the Data

The analysis began with an in-depth study of the interview transcripts. This stage involved iterative reading to identify significant patterns and initial areas of interest. Perceptions of participants were recorded, namely those that demonstrated varying degrees of confidence in the predictive model, preferences for data presentation, and difficulties associated with EV charging. Furthermore, upon concluding this phase, similarities and differences among participants' opinions were emphasized, in order to adequately prepare for the subsequent phase.

#### 4.2.2. Generating Initial Codes

The data was systematically coded, with codes such as "trust in predictions", "graphical preference", "planning importance", and "accuracy concerns" emerging. These codes served as the building blocks for the development of broader themes. Initially, the researcher generated as many codes as possible, then carefully sorted and reduced the codes to fully represent the participants' views and answers.

#### 4.2.3. Searching for Themes

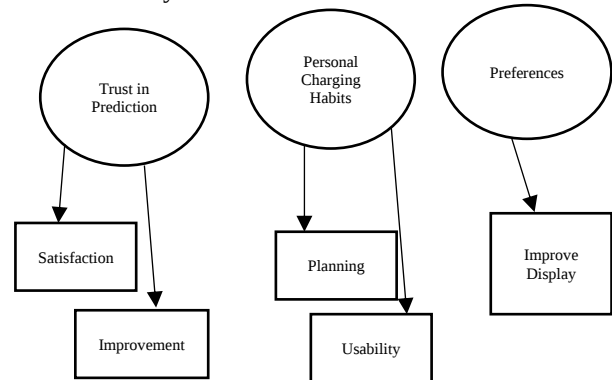
The initial codes were organized into potential themes. For example, codes related to trust and conditional acceptance of the model's predictions were grouped into the theme "Conditional Trust in Predictive Models". Similarly, codes on data representation preferences were grouped under "Preference for Data Representation".

#### 4.2.4. Reviewing Themes

The themes were refined to ensure they accurately captured the data's essence. Some themes were merged, while others were further subdivided. For instance, the theme "Challenges with Predictive Accuracy" was refined to capture specific concerns about the model's ability to handle unexpected events.

#### 4.2.5. Naming Themes

Three key themes were identified and defined, each of which has some sub-themes as discussed below. The identified key themes and sub-themes are shown in



**Fig. 5** below.

##### 4.2.5.1. Charging Habits

Most interviewees tended to combine charging stops with break times on longer journeys, minimizing inconvenience. Unplanned or extended trips caused the most difficulty, highlighting infrastructural and planning gaps.

##### 4.2.5.2. Display Format Preferences

Participants were shown three types of display:

- **Graphical** (Scenario 1): Universally deemed informative, allowing quick recognition of trends and occupancy fluctuations. Suggestions included adding charging speeds or plug types.
- **Textual** (Scenario 2): Preferred by some for straightforward interpretation, especially for a shorter horizon. However, many felt text formats could miss nuances about rapid changes in occupancy.
- **Categorical** (Scenario 3): Perceived as too broad without exact numeric values. Several recommended combining categories with numeric indications (e.g. "8 spaces – moderately busy").

##### 4.2.5.3. Trust in Model Predictions

From the participants' perspectives on the interview questions, we found out that the trust levels are varied as follows:

- **High Confidence:** Minor discrepancies between predicted and actual occupancy did not troublesome; they appreciated any tool that guided them in planning.
- **Conditional Acceptance:** Others would cross-check predictive outputs with current or real-time data, especially if they had urgent charging needs.

- **Weak Confidence:** A few participants doubted the model's ability to account for traffic accidents or unexpected surges in demand. They stressed the need for real-time updates and contextual alerts.

Key factors influencing trust included:

- **Accuracy Over Time:** Users wanted predictions to consistently reflect reality, acknowledging that minor deviations were acceptable but large discrepancies eroded confidence.
- **Transparent Assumptions:** If users understood how predictions were generated, such as accounting for peak hours or historical data they were more likely to trust the tool.
- **Contextual Clarity:** Additional details (e.g. charging speed, total slots, live occupancy) supported more informed decisions and reassured users that the model accounted for real-world variables.

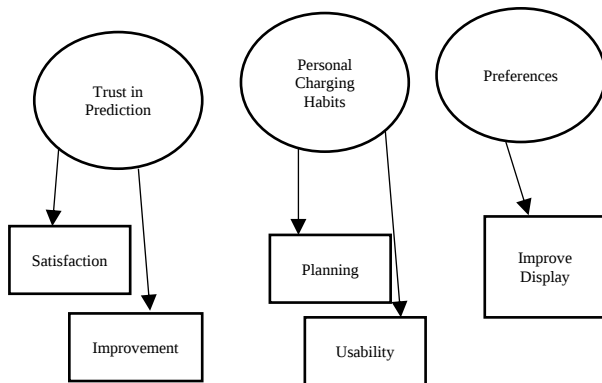


Fig. 5. The Final thematic Map of The Performed Thematic Analysis

## 5. Discussion

Participants' display expectations highlight the need for designs that balance clarity, flexibility, and depth. Charts were popular due to their capacity to reveal patterns and future changes visually. However, certain users favour textual summaries for quick scanning.

The overall hesitance towards purely categorical outputs indicates that many drivers rely on subtleties of numeric information, especially as EVCS occupancy can fluctuate quickly.

Implications for Practice include:

- **User-Centric Tools:** Predictive platforms should integrate real-time data (including exogenous events) while maintaining transparency about forecasting uncertainty.
- **Adaptive Display Formats:** Allow EV owners to toggle between a concise view (perhaps text-based) and a more detailed graphical representation with numeric predictions.
- **Personalisation and Education:** Beginners might benefit from more guidance and reassurance (e.g. prompts or alerts if battery range is limited), helping them build trust in predictive tools over time.

## 6. Conclusion

This study is set out to address:

- What display expectations do EV owners prefer to see for EVCS occupancy prediction?
- What are the key factors that influence EV owners' trust in predictive models as a source to manage their charging times?

The results suggest that graphical displays (especially bar and line charts) are widely perceived as clear and comprehensive.

Table 2 Summary of Thematic Analysis.

| Theme/subtheme                            | Description                                                                                                       | Participant Excerpt                                                                                  |
|-------------------------------------------|-------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| <b>Charging Habits</b>                    |                                                                                                                   |                                                                                                      |
| Planned Stops                             | Charging stops are often planned for long journeys and are seen as non-intrusive.                                 | "I plan stops for comfort during long journeys". [P1]                                                |
| Unplanned Struggles                       | Struggles arise primarily during unplanned or extended journeys.                                                  | "Struggles arise only when the trip exceeds the battery range". [P5]                                 |
| <b>Preference for Data Representation</b> |                                                                                                                   |                                                                                                      |
| Graph Display                             | Preferred for clarity and ability to show trends over time.                                                       | "Graphs provide an overall sense of busyness at a glance". [P1], [P10]                               |
| Text Display                              | Preferred by some for simplicity, particularly in short-term scenarios or while traveling.                        | "Text is easier to interpret on the go". [P2], [P4]                                                  |
| Categorical Display                       | Less favoured; participants emphasized the need for precise numerical data.                                       | "Numbers are clearer and help in decision-making compared to categories". [P1], [P3]                 |
| <b>Trust in Model Prediction</b>          |                                                                                                                   |                                                                                                      |
| High Level of Confidence                  | Participants accepted predictions, even with some inaccuracies, finding them helpful for decision-making.         | "The predictions are close and acceptable as a means to help make decisions". [P1], [P2], [P10]      |
| Partial Confidence                        | Participants used predictions cautiously, combining them with prior knowledge or considering situational urgency. | "Predictions are useful, but I would also consider live data or the situation's urgency". [P3], [P6] |
| Weak Confidence                           | Some expressed distrust, particularly due to the model's inability to account for unexpected events.              | "Unexpected events can make predictions unreliable". [P8]                                            |
| Unexpected Events                         | Real-world variables, like accidents or demand surges, undermine prediction reliability.                          | "Predictions can't account for all real-world variables". [P8]                                       |
| Lack of Contextual Information            | Adding data about charging plug types and speeds could enhance decision-making.                                   | "Knowing plug types would help refine predictions and decisions". [P3], [P5]                         |

Textual or hybrid approaches can be useful for short-term or on-the-go reference, so long as they include sufficient detail about station capacity and availability trends. By contrast, purely categorical labels are often dismissed as too vague. Trust emerges from consistent accuracy, transparency about assumptions, and contextual completeness (charging speed, plug types, and real-time occupancy updates). While many participants are willing to rely on model predictions, they are likely to do so when they can verify or supplement forecasts with real-time data or personal experience. Designers and stakeholders seeking to encourage EV usage should therefore consider these insights to help ensure higher adoption of predictive tools.

Future iterations of predictive models could benefit from incorporating additional external data—such as live traffic, weather events, or major public gatherings—to handle sudden shifts in charging demand. Studies could also examine how different user segments (e.g. rural vs. urban, new vs. long-term EV owners) might require tailored display formats, leading to more intuitive, trustworthy, and inclusive systems.

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