CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

As the electrification of urban transportation accelerates worldwide, it becomes increasingly important to understand the behavioral patterns of electric vehicle (EV) users. Among them, low state-of-charge (SOC) driving behavior, defined as driving with less than 20% battery charge,remains understudied. This chapter reviews existing research around EV usage, chargingbehavior, and predictive models, identifies methodological and empirical gaps, and places our study in the broader context of sustainable EV operations and user behavior modeling.

Review is organized around the following themes:

(a) What has been done to model EV user behavior?

(b) What data and methods are used?

(c) What challenges remain in low-SOC behavior?

(d) How does our project advance the frontier with machine learning and interpretability?

2.2 Modeling EV Usage: Dominant Paradigms

Most EV-related research falls into a few main modeling categories:

(a) Route Optimization. The models in this category (e.g., Li et al., 2021) aim to find the best path with less energy consumption or travel time. They are rational and risk-averse. Hence, low-SOC behavior can be treated as an outlier.

(b) Charging Station Recommendations. Guo et al. (2021) & Co. aim to find the optimal geographic distribution of chargers according to their usage times or predicted demands. These approaches improve the infrastructure planning, but they do not model the low SOC behavior on the user side.

(c) Charging Station Recommendations. Chen et al. (2021) & Kim et al. (2020) utilize time-series models or machine learning models to forecast the total electricity or station demands. These models are useful for grid management, but they ignore the individual-level irregularities of low-SOC behavior

(d) Behavioral Analyses with Limited Scope. Zhao et al. (2022) is one of the few works that considers the low-SOC behavior. Their method is mainly descriptive, and the authors claimed that the best prediction accuracy was 38.4%, without applying interpretable machine learning methods.

2.3 State-of-the-Art in Predictive and Interpretable Modeling

State-of-the-art machine learning methods have increasingly been applied in transportation analytics. These include the eXtreme Gradient Boosting method (XGBoost) and random forests (Kim et al., 2020) for classification tasks, and SHAP (SHapley Additive exPlanations) (Lundberg & Lee, 2017) for post-hoc explanation of decisions made by any machine learning model.

These methods have been applied scarcely in user-specific EV behavior prediction, let alone in low-SOC-to-charging transitions. Our project is unique in the sense that both prediction and explanation are made possible not just to indicate when a user is likely to charge, but also to explain why.

2.4 Empirical Foundations: Data Sources and Their Limitations

Different data strategies dominate the field:

Dataset Type	Description	Limitation
Synthetic simulations	Modeled trips based on assumptions	Lack behavioral realism
Charging logs	Timestamped records from charging stations	No context of trip or SOC before charging
GPS + Driving logs	High-resolution telemetry data	Often proprietary or short-term
UrbanEV Dataset (this study)	Real-world, multi-month trip + SOC data	Ideal for behavioral, temporal, and ML analysis

The UrbanEV dataset, employed in this research, is unique and interesting due to the richness of the information available over thousands of EVs for 6 months. The data includes time-stampedtrip information, SOC information, and charging behaviors which are important for low-SOC driving event detection and modeling with fine-grained information.

2.5 Behavioral and Temporal Characteristics of Low- SOC Events

Very few studies have explored the when and why of low-SOC driving. However, such behaviors do have impacts: increased battery degradation, unexpected trip interruptions, and charger overcurrents. Our work contributes the following:

(a) At the hourly, daily and weekly level, when do L-SOC users exhibit low-SOC behavior?When you click Online Video, you can paste in the embed code for the video you want to add.

(b) How do trip characteristics vary between L-SOC and N-SOC use?

(c) How to simulate immediate vs delayed SOC post-charging behavior?

Some temporal pattern studies (Wang et al., 2022) are relevant, but rarely consider SOC thresholds or individual responses

2.6 Interpreting Predictions: The Role of SHAP

Current black-box models are opaque. To gain trust and use predictions, interpretability is key. With SHAP we can:

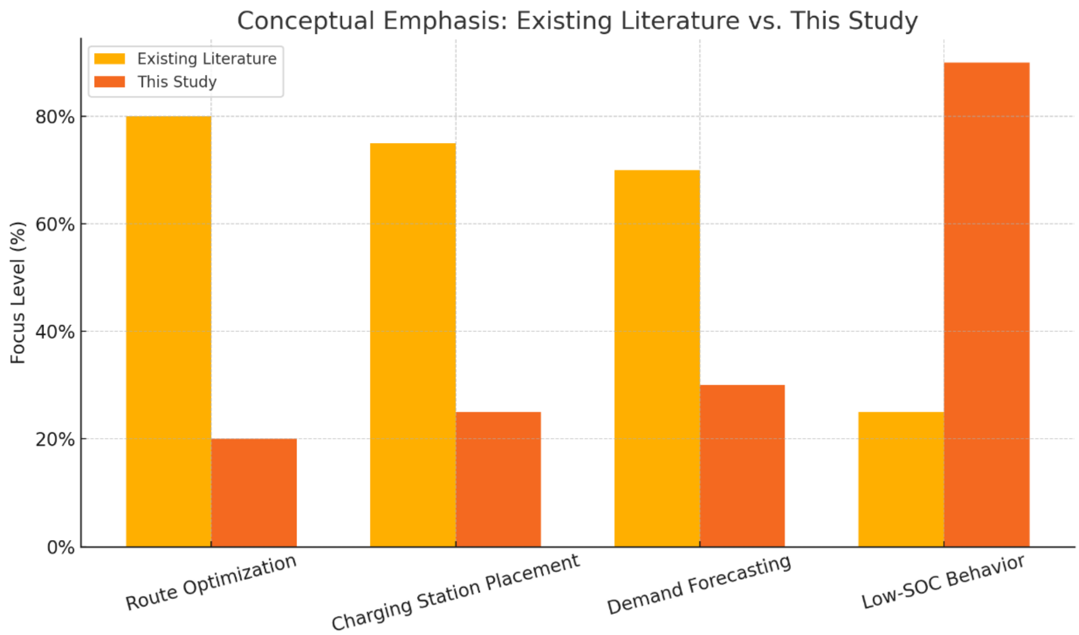
(a) Measure how much each feature contributed to a specific prediction.

(b) Discover which variables are most important (e.g. hour of day, previous charging interval, trip length, etc..).

(c) Create explainable alerts/policy outputs (e.g. why some users always delay charging?).

2.7 Conceptual Gap: Where Our Study Fits

The imbalance in research attention is reflected in:



(a) Existing literature places heavy emphasis on planning and optimization.

(b) Low SOC behaviors are marginalized and treated as noise or exceptions.

(c) This study repositions low SOC behaviors as core behavioral and operational concerns.

Provides deeper insights and practical implications by providing prediction + explanation tools at the event level.

2.8 Summary and Research Directions

To summarize:

(a) Existing literature mainly focuses on optimization and infrastructure construction, ignoring the real-world usage patterns with low SOC.
(b) Existing behavior prediction models lack transparency and cannot address post-SOC behavior.
(c) This study uses the UrbanEV dataset to address this gap through predictive models and explainable AI tools.
(d) It contributes both in terms of methodology (event-level modeling + SHAP) and practice (targeted support for high-risk users or locations).

Future research directions may include:

(a) Use weather / incentive / POI data to improve model robustness.construction, ignoring the real-world usage patterns with low SOC.
(b) Implement alert or intervention in a real-time implementation.
(c) Conduct cross-cultural study or in different urban context.