CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

This study aims to predict the behavior of electric vehicle (EV) drivers after a battery low-charge (SOC) event occurs, specifically, the possibility of whether they will make an immediate charging decision after the battery runs low. The study employed a method combining machine learning and explainable artificial intelligence to analyze a dataset containing over 100,000 real travel records and simulate users' responses to related situations when the battery is extremely low.

The research results indicate that the immediate charging behavior after low battery levels is influenced by multiple interacting factors, including the battery state of charge (SOC) at the end of the trip, the total distance traveled, the time of day, and the frequency of charging. It is notable that evening trips and scenarios with low battery levels but longer distances significantly increase the likelihood of charging. By using XGBoost for powerful feature extraction and classification, the prediction model achieved a high accuracy rate (87%) and a high AUC score (0.90), confirming that the model can capture the real behavioral trends.

The integration of SHAP also provides transparent explanations for the model's output. This enhanced interpretability helps reveal the hidden logic behind user behavior, identifying that drivers with lower battery charge levels, fewer recent charging sessions, and longer travel times are more likely to charge immediately. These insights not only validate the reliability of the prediction system but also offer opportunities for the planning of new energy charging station construction.

The main contributions of this study are threefold. Firstly, it has developed a data-based framework to describe the behavioral characteristics of low-power driving during the use of electric vehicles. Secondly, it demonstrates that the behavior perception prediction model can achieve high accuracy and transparency, thereby establishing a connection between predictive analysis and decision support. Finally, this study showcases the potential of interpretable models in guiding the deployment of intelligent charging infrastructure and in the research of electric vehicle policies. These contributions are of practical significance for vehicle research and manufacturing enterprises, urban transportation planners, and intelligent energy systems.

5.2 Future Works

Although the current research has achieved encouraging results, it must be acknowledged that there are still some limitations. The model has not yet incorporated factors such as space, environment, or external policies that may affect charging behavior. Additionally, no sufficient research has been conducted on the temporal dynamic changes in behavior evolution over multiple days or usage cycles.

Future research directions include:

Integration of geographic data and infrastructure data: Incorporating elements such as geographical location information, the availability of nearby charging stations, and regional charging costs into the consideration scope will help address issues in the decision-making process more comprehensively.

Incorporation of environmental factors: External factors such as temperature, traffic congestion conditions, and weather conditions have been proven to affect battery consumption and the urgency of charging. If these factors are taken into account, they will be of great value.

Time-based behavior modeling: Using time-aware recurrent models or architectures can capture users' charging habits and deviations over longer periods, thereby enhancing the degree of personalization.

Adaptive decision support systems: Embedding the prediction engine into the on-board real-time system can generate proactive charging reminders, route re-planning, or dynamic battery charging status warnings based on driver behavior. 5. Policy optimization and simulation: The model can perform infrastructure planning based on simulations, which is helpful for identifying underserved areas, predicting demand hotspots, and evaluating the response effects of different charging incentive measures.

In summary, this research lays the foundation for the design of behavior-based electric vehicle systems. The predictive model is built based on actual usage behavior and demonstrates significant potential for contributions in intelligent electric vehicle management, user-centered travel services, and urban sustainable development strategies.

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Appendix A Sample entries from the EV trip dataset

Contains representative rows of the structured dataset used for model training and evaluation. Fields include:

trip_start_time: Timestamp when the trip began

trip_end_time: Timestamp when the trip ended

soc_end: Final state-of-charge percentage at trip end

trip_distance: Distance driven in kilometers

next_charge_time: Time when the next charging session began

charged_immediately: Binary label indicating if charging started promptly (1) or not(0)

Appendix B Hyperparameter configuration for XGBoost

The XGBoost classifier was optimized using the following parameter values:

objective: ‘binary:logistic’

eval_metric: ‘auc’

eta: 0.1

max_depth: 6

subsample: 0.8

colsample_bytree: 0.8

num_boost_round: 100

early_stopping_rounds: 10

These parameters were selected based on empirical testing to balance accuracy and generalization.