engineering proceedings

Proceeding Paper

A CSMF- and LLM-Based Hybrid Approach for Charging Station Recommendations in Electrical Vehicle Networks †

Yusuf Eymen Sezen [1], Muhammad Jamil [1,2], Adnan Kavak [1,2,*], Sema Bayraktar [2] and Günay Aslan [2]

[1] Department of Computer Engineering, Kocaeli University, 41001 İzmit, Türkiye; 245112060@kocaeli.edu.tr (Y.E.S.); jamil138.amin@gmail.com (M.J.)
[2] Wireless Information and Intelligent Systems (WINS) Research Center, Kocaeli University, 41001 İzmit, Türkiye; bayraktar.sema41@gmail.com (S.B.); gunay.aslan@kocaeli.edu.tr (G.A.)
* Correspondence: akavak@kocaeli.edu.tr
† Presented at the International Conference on Electronics, Engineering Physics and Earth Science (EEPES2026), Bandirma, Turkey, 24–27 June 2026.

Abstract

This study introduces a hybrid framework that combines Multi-Agent Reinforcement Learning (MARL) based on Mean Field Theory (CSMF) with Large Language Models (LLMs) to provide optimized and explainable charging station recommendations for EV users in Turkey. By integrating real-time data from 11,702 stations and 30,941 sockets via the Energy Market Regulatory Authority of Türkiye (EMRA) API, the system captures dynamic information on station availability, socket types, charging power, and pricing, enabling context-aware, user-centric guidance. The proposed architecture follows a Centralized Training and Decentralized Execution (CTDE) framework, in which multiple agents make local decisions while a centralized critic evaluates global states to improve policy learning and reduce congestion. CSMF reduces computational complexity and lowers the average waiting time by 71.8%, while the LLM component translates technical optimization outcomes into human-readable explanations, enhancing trust and transparency. A React Native mobile application demonstrates end-to-end usability, allowing users to filter stations by distance, cost, socket type, and green energy usage, with real-time availability updates. Experimental results show that the hybrid CSMF + LLM approach achieves a 100% Available Facility Rate (AFR) while maintaining low response time (180 ms), outperforming conventional nearest-station, random, and basic MARL methods. By combining technical efficiency with explainable recommendations and real-world deployment, this study presents a scalable, practical, and trustworthy solution for EV charging infrastructure management, offering both academic contributions and a ready-to-use application for drivers.

Keywords: electric vehicles; EV charging stations; multi-agent reinforcement learning; explainable artificial intelligence; large language models; mean field theory

Check for updates

Academic Editors: Teodor Iliev, Ivaylo Stoyanov, Grigor Mihaylov and Selahattin Kosunalp

Published: 2 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

The transportation sector's electrification process has accelerated in order to mitigate the effects of global warming and protect the environment [1–3]. During this process, the market for electric vehicles has been expanding rapidly worldwide. In Turkey, it is growing annually by 40%. However, there are significant logistical challenges associated with this growth. Unlike fossil fuel vehicles, current EV technologies have a limited range of approximately 200 to 500 km, and charging these vehicles can take anywhere from

30 min to several hours. Because of this, drivers experience "range anxiety" [4]. There is also a lack of planning and spatiotemporal imbalance among the current stations, and the infrastructure for charging has not yet reached a sufficient level [5]. Because there are not many options for home charging, users are reliant on public stations. Current mobile apps typically do not provide real-time data, cannot generate personalized recommendations, and do not explain why a station is suggested. Due to variations in regional density or users being redirected to closed or occupied stations, this results in lengthy lines at stations. In Turkey, there are 30,941 outlets and 11,702 operational charging stations as of 2024, with over 150 different brands and operators offering services [6]. Despite the sector's complexity, 67% of users report having trouble locating the "nearest and available" station. The great majority of research in the literature is based on simulations using data from different cities. The main driving force behind this project is the dearth of scholarly research utilizing real-time data at the scale of Turkey. Increasing driver trust in the system also depends on removing AI models from the "black box" structure and presenting them to users using Explainable AI (XAI) principles [7]. Within the scope of the study, answers to the following questions are sought:

1. How do multi-agent (MARL) algorithms receive dynamic input from real-time data from the EMRA API?
2. How do Large Language Models (LLMs) convert technical optimization outcomes into user-friendly explanations?
3. What is the difference in performance between simulation-based literature examples and a hybrid system operating with real-world data?
4. How should an end-to-end system's architecture be created so that drivers can utilize it on their regular routes?

The four primary contributions this study makes to the field of literature and applications are as follows: First Comprehensive Study Concentrating on Actual Data: While studies in the literature usually focus on small or artificial datasets, this study is the first comprehensive investigation tested on 11,702 stations throughout Turkey with **EMRA** API integration.

- **CSMF and LLM Hybrid Approach:** Mean Field Theory, which lowers computational cost, and LLMs with natural language processing capabilities provide both technical efficiency and explainability.
- **Available Facility Rate Success:** By guiding the user to a socket that is unquestionably available in every tested scenario, the developed algorithm offered a 100% available station finding guarantee.
- **End-to-End Application for Practical Use:** In addition to offering a theoretical model, a mobile application prototype with map integration that was created with React Native and that drivers can directly experience has been presented.

2. Related Work

The rapid growth of electric vehicles (EVs) has increased the need for efficient charging station infrastructure. Traditional greedy or random algorithms often fail to optimize multiple factors simultaneously, such as distance, price, and availability [8,9]. Recent studies use Multi-Agent Reinforcement Learning (MARL) to handle complex charging scenarios, while hybrid approaches with Large Language Models (LLMs) and Explainable AI (XAI) improve interpretability for users [10,11]. One of the first studies utilizing the MARL framework to handle inadequate infrastructure and uneven demands in the field of electric vehicle charging recommendation was presented by the authors of [12]. The Centralized Training and Decentralized Execution (CTDE) architecture has been explored in many studies in the literature. Data during training reached all agents and achieved a global perspective.

During the execution state, each agent makes its own decisions with local observations. The authors of [13] proposed the Charging Station Recommendation Algorithm using Mean Field Theory (CSMF) to reduce the computational complexity of large-scale EV charging recommendation systems. In this approach, each agent makes decisions based on its own action, the global state, and the average actions of neighboring agents. By approximating multi-agent interactions through a mean-field representation, the model simplifies decision-making in large-scale charging networks. The main objective of this model is to manage complex charging states in large-scale EV networks. The CSMF model reduces the Total Mean Waiting Time (TMWT) and has shown competitive performance compared with existing methods in the literature. By concentrating on spatiotemporal analysis, this model was able to cut the average waiting time by 58.9%. It improved system stability and expedited policy learning by incorporating an "imitative learning" scheme. The Multi-Agent Deep Deterministic Policy Gradient (DDPG) approach outperforms the single-agent DDPG approach by 16.1%, making it a popular baseline model. The authors of [14] integrated imitation learning with PPO-based DRL (Proximal Policy Optimization-based Deep Reinforcement Learning) for energy management, achieving 95.59% of global optimal cost and reducing training steps by 51.69% compared to standalone PPO. The authors of [15] proposed a statistics-based algorithm to reduce the grid harmonics caused by EVs, which are essentially non-linear loads. Their proposed algorithm helped in reducing the grid harmonics by phase-shifting the carrier waves of each charging bay within a charging station. When the carrier waves are phase-shifted, the switching transients are distributed over time and some of the generated harmonics will cancel each other. Their technique does not require any centralized communication or information exchange between the charging bays to coordinate the carrier waves. Their algorithm is implemented in twenty (20) bays within a charging station by utilizing the Mean and Variance values of the Cumulative Poisson Distribution. They implemented their research using the MATLAB R2026a Simulink platform and the performance is validated. The techniques have demonstrated a 30% improvement in the power quality of the grid voltage. Table 1 presents a comparative summary of related studies and the proposed approach.

Table 1. Comparison of existing EV charging station recommendation studies with the proposed approach.

Ref. No.	Algorithm	Data Source	Station Count
[12]	MARL	Pekin/Shanghai Sim.	50
[13]	ST-MARL	Chiang Mai city	50
[14]	Imitation Learning	West Virginia University Interstate	100
[15]	Mean Field	MATLAB Simulink	20
Proposed	**CSMF + LLM**	**EMRA API**	**11,702**

The models' effectiveness has typically been evaluated in simulation environments with a small number of stations in the reviewed literature (MASTER, CSMF, RLCharge, etc.). No study has used real-time datasets from a national data network (such as EPDK) on a scale of more than 11,000 stations. Additionally, a major gap in the literature is the lack of an Explainable AI (XAI) layer that provides a natural language explanation of recommendation system decisions to the user and an end-to-end mobile application integration that drivers can use directly. By combining LLM-based explainability with actual data from Turkey, this study seeks to close this gap.

3. Research Methodology

This study proposes a comprehensive framework to address range anxiety and challenges in locating EV charging stations. It integrates theoretical models from the literature with real-time data and explainable artificial intelligence. The proposed system leverages Mean Field Theory to reduce computational complexity and employs large language models (LLMs) to generate meaningful, user-centric recommendations.

3.1. Overview and Design Principles

The system architecture is designed as a three-layer microservice structure to support modularity, scalability, and low-latency operation. It adapts the Centralized Training and Decentralized Execution (CTDE) principle to a real-time EV charging recommendation environment. The front-end layer enables users to interact with the system and transfers dynamic variables, such as GPS location and vehicle battery status, to the back-end services. The orchestration layer coordinates data exchange among the mobile application, EPDK data services, and Python (3.12 version) based AI modules. During the design process, scalability, low latency, and high availability were considered fundamental requirements. Figure 1 shows the overall system architecture.

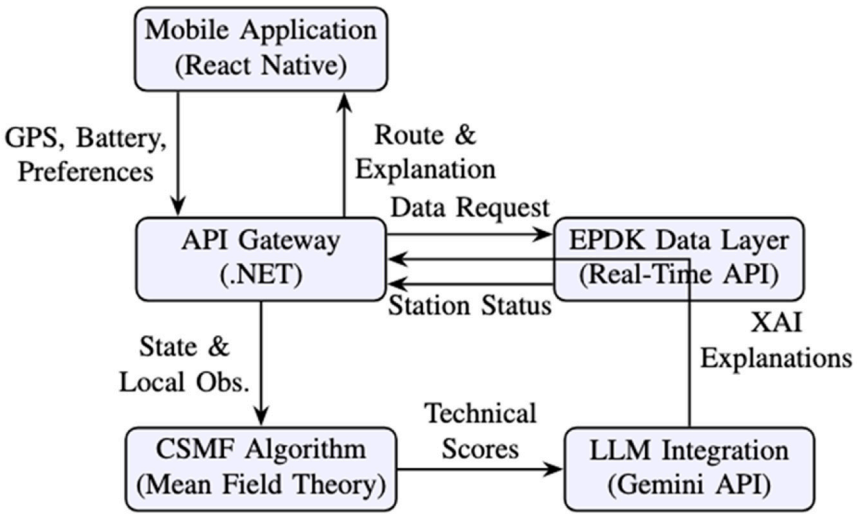


Figure 1. System Architecture for Hybrid CSMF and LLM Recommendation.

3.2. Energy Market Regulatory Authority Data Layer

Unlike most studies in the literature, which rely on static simulation data from selected cities, this study uses real charging network data from Türkiye. The system retrieves data for 30,941 sockets and 11,702 stations through the EMRA (Energy Market Regulatory Authority) API. The API provides real-time information about socket status, including FREE, IN USE, and RESERVED states. Additional parameters, such as charging price (TL/kWh), socket type (AC, DC, or AC/DC), charging power (kW), and station distance, are used as inputs for the recommendation model. A five-minute caching strategy is applied to reduce API loading time and improve system responsiveness. Geographical proximity between the user and charging stations is calculated using the Haversine formula, which enables efficient distance-based filtering.

3.3. Mathematical Modeling of the CSMF Algorithm

The charging station recommendation problem is formulated as a Multi-Agent Markov Decision Process (MAMDP). To mitigate the curse of dimensionality as the number of agents, N, increases, we apply Mean Field Theory to approximate the joint action of the fleet.

https://doi.org/10.3390/engproc2026154042

3.3.1. State and Action Space

The state of agent i at time t is defined as $s_i^t = p_i^t, b_i^t, K_t$, where p_i^t represents the GPS coordinates, b_i^t is the current State of Charge (SoC), and K_t is the real-time metadata (availability, price, power) retrieved via the EMRA API. The action $a_i^t \in A$ corresponds to the selection of a specific charging station from the set of M candidates.

3.3.2. Mean Field Approximation and Action Space

In the CSMF framework, the Q-function for agent i is factorized using the average action $\bar{a}_t$ of neighboring agents. The global interaction is approximated by the following:

$$Q_i(s, a_1, \ldots, a_N) \approx Q_i(s, a_i, \bar{a}_i) \tag{1}$$

where the Mean Field $\bar{a}_i$ is the empirical distribution of actions within the agent's neighborhood $N(i)$:

$$\bar{a}_i = \frac{1}{Ni} \sum_{j \in N(i)} a_j \tag{2}$$

This allows the Actor network to update its policy π_θ using the Mean Field Actor–Critic gradient:

$$\nabla_\theta J(\theta) = E_{s,a\sim\pi}[\nabla_\theta \log \pi_\theta (a_i | s_i, \bar{a}_i) Q_i(s, a_i, \bar{a}_i)] \tag{3}$$

3.3.3. Reward Function Design

The agent aims to maximize a multi-objective reward function R that balances user-centric and system-wide goals:

$$R = \alpha \cdot \text{Avail} - \beta \cdot D(p_i, p_{dest}) - \gamma \cdot C + \delta \cdot \zeta \tag{4}$$

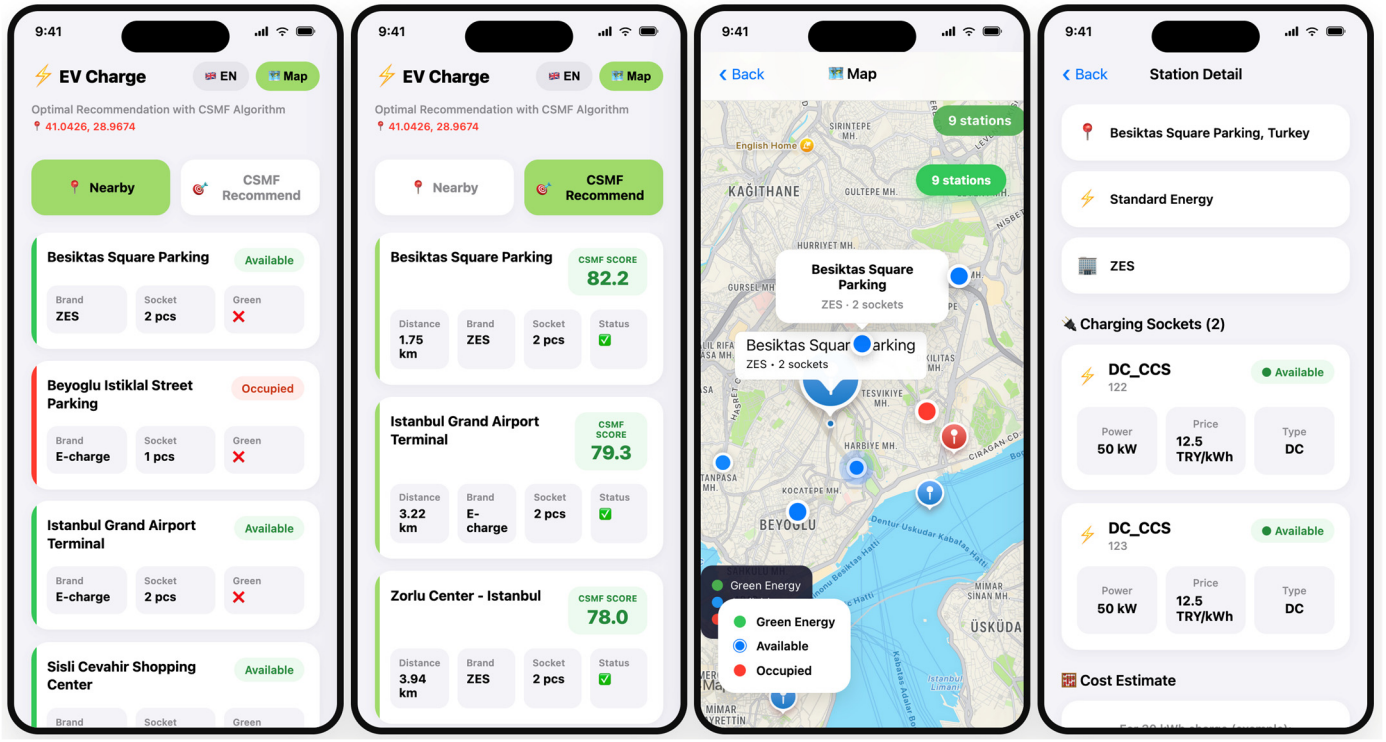
where $D(\cdot)$ is the Haversine distance, C is the cost per kWh, and ζ is a binary indicator for green energy. The coefficients $\alpha, \beta, \gamma, \delta$ are weights assigned to prioritize the AFR.

3.4. LLM-Based Explainable AI (XAI) Integration

The primary innovation of this framework is the integration of a Large Language Model (LLM) layer to transform the technical scores generated by the CSMF algorithm into human-comprehensible explanations. While MARL models often function as "black boxes," our approach ensures grounding by passing a structured tuple $E = K, \vec{R}$ to the Gemini API, where K is the verified EMRA station metadata and $\vec{R}$ is the normalized reward vector. This ensures the LLM justifies its recommendation based strictly on technical parameters like cost, speed, and green energy, preventing model hallucinations.

3.5. Mobile Application Features

The system is realized through a mobile application created on the React Native Framework (version 0.87.1), featuring an interactive map where stations are dynamically color-coded based on real-time availability. The user can apply custom filters for price, socket type, and green energy usage. As shown in Figure 2, the application provides localization support and prioritizes user experience through low-latency responses. The complete code of mobile application can be accessed through our GitHub Repository using this link: https://github.com/EymenSezen/EVMobile (Public Repository, accessed on 25 May 2026).



(**a**) (**b**) (**c**) (**d**)

Figure 2. The Mobile App Recommendation interface showcasing map visualization and detailed charging station justifications: (**a**) real-time charging stations displayed on the map; (**b**) detailed recommendation screen with station information; (**c**) route-based station selection view; (**d**) LLM-generated explanation for the recommended charging station.

3.6. Dataset Features

This study uses real charging station data obtained from the EMRA Charge Data API. The dataset includes 30,941 charging points and 11,702 active charging stations across Türkiye. The API covers multiple charging operators and brands operating in the Turkish EV charging market. The test scenarios were designed using areas with high charging demand to evaluate the performance of the recommendation system under realistic conditions.

3.7. Comparison Techniques

To evaluate the system's performance beyond the standard Mean Charging Waiting Time (MCWT) and Charging Failure Rate (CFR) found in the literature, we utilize the following indicators:

- Available Facility Rate (AFR): This is the proportion of recommended stations that are confirmed as "FREE" via the EMRA API at the moment of suggestion. This directly measures the reliability of the recommendation.
- Average Minimum Distance (AMD): This is the mean Haversine distance (in km) between the user's real-time GPS coordinates and the suggested charging facility.
- Response Time (RT): This is the end-to-end system latency, measured in milliseconds, from the user's request to the delivery of the LLM-generated explainable recommendation.
- Explainability Score (χ): This is a qualitative metric ranging from 1 to 5, used to assess the linguistic clarity and technical grounding of the natural language explanations generated by the hybrid layer.

https://doi.org/10.3390/engproc2026154042

3.8. Evaluation Metrics

Five different approaches were compared in order to demonstrate the efficacy of the proposed hybrid model: (1) Nearest: Conventional approach based solely on Haversine distance; (2) Random: a "baseline" approach based on random selection without any optimization; (3) Simple CSMF: a simplified model that solely takes instant availability score and distance into account; (4) CSMF: Mean Field Actor–Critic implementation with full scope; and (5) CSMF + LLM (Proposed): Hybrid approach that combines the explainability of LLM with the technical success of CSMF. Table 2 shows the results and performance of different charging station recommendation methods.

Table 2. Results and performance of different charging station recommendation methods.

Method	AMD (km)	AFR (%)	RT (ms)
Nearest	0.26	100.0	0.4
Random	5.90	90.0	0.01
Basic CSMF	0.71	100.0	1.1
CSMF	0.72	100.0	5.1
CSMF + LLM	**0.72**	**100.0**	**180**

4. Discussion

This section discusses the theoretical and practical implications of the proposed system and analyzes the experimental results by comparing them with previous studies in the literature. The most notable finding of the study is that the proposed system achieved 100% AFR success across ten different test locations in Istanbul. This result demonstrates the reliability of the system, especially considering that well-known models in the literature such as MASTER (3.17% CFR) and RLCharge still report small failure rates. Most studies in the literature rely on simulation datasets from cities such as Shanghai, Beijing, and Berlin. In contrast, this study evaluates the effectiveness of theoretical models under real-world conditions (traffic, instant occupancy, and operator diversity) using 11,702 real charging station records obtained via **EMRA**. Through LLM integration, the system not only provides routing recommendations but also explains the reasons behind station selection (price, green energy, charging speed, etc.), which adds a psychological layer of trust to the goal of reducing range anxiety. The CSMF algorithm uses a Mean Field approach by considering the average behavior of other agents, which reduces computational complexity as the number of agents increases. This enables the system to operate efficiently across a large-scale network of 11,702 stations in Turkey. Experimental results also show that simple methods such as the Nearest strategy can achieve 100% AFR in Istanbul due to the relatively high station density (5+ stations per km^2). However, the literature indicates that coordinated strategies (CSMF/MARL) reduce costs by 26% and improve success rates by 9% in worst-case scenarios where demand increases, or station density is low. Therefore, unlike simple approaches, CSMF-based routing can prevent congestion in lower-density regions of Anatolia or during peak hours (17:00–20:00). When the LLM layer was added, the system response time increased to 180 ms due to network latency from the Gemini API. Although the AMAAC algorithm in the literature reports decision times as low as 23 ms, a latency of 180 ms (0.18 s) remains practically unnoticeable for mobile application users. In return, the system gains explainability and personalized recommendations, which directly support the user-centric design direction suggested in previous studies. Response time can be further reduced by using caching strategies for frequently requested locations and user profiles.

The proposed hybrid architecture provides a balanced and scalable solution combining computational efficiency (CSMF) and human–machine interactions (LLM). Using real-time

data from Turkey, the CSMF + LLM hybrid system achieved 100% AFR performance; however, several limitations remain. The accuracy of data retrieved from the **EMRA** API is critical, as potential delays or technical issues may affect the real-time status of stations (FREE/IN_USE). Future work will consider integrating offline prediction models to handle data interruptions. In addition, many studies evaluate performance using metrics such as Mean Charging Waiting Time (MCWT) in simulation environments. While similar metrics were used here, validating waiting times in real-world scenarios requires actual user data from vehicles or station sensors. Furthermore, although LLM-generated explanations are expected to increase user trust, this study did not include a large-scale A/B test or user satisfaction survey. Future work should quantitatively evaluate driver satisfaction in Turkey. In the current implementation, the model calculates distances using the Haversine formula. However, real travel time and charging decisions are also influenced by traffic density. Future improvements will integrate real-time traffic data from Intelligent Transportation Systems (ITSs) to enhance ETA estimation and routing accuracy.

5. Conclusions

This study introduced a novel recommendation system to alleviate range anxiety and challenges faced by electric vehicle (EV) users in locating charging stations using real-time data at the scale of Türkiye. As the EV market expands rapidly both locally and globally, efficient utilization of limited existing infrastructure becomes essential. Using data from 11,702 stations and 30,941 sockets accessed via the EMRA API, the developed system integrates the explainability of Large Language Models (LLMs) with a Charging Station Recommendation Algorithm based on Mean Field Theory and Multi-Agent Reinforcement Learning (MARL). The proposed approach successfully generated reliable charging routes, achieving 100% AFR across all test scenarios. Key contributions include the first comprehensive study using Türkiye's official charging network data, whereas the prior literature largely relies on limited simulation datasets. For the first time, an LLM-based explainability layer was integrated with Mean Field Theory, reducing computational costs while maintaining efficiency in large-scale agent systems and combining user-centric communication with technical optimization. Beyond a theoretical model, a fully integrated system comprising a Python-based AI service, a NET-based API Gateway, and a React Native mobile application was designed and prototyped. The system explains "why this station was recommended" in natural language based on cost, charging speed, availability, and green energy usage, improving transparency and reducing the black-box nature of MARL-based recommendations.

To support future research, the codebase and anonymized datasets will be made available to the scientific community. By combining explainable AI with real-time analytics, this study advances EV infrastructure management and offers a scalable solution for smart city transportation systems.

Author Contributions: Conceptualization, Y.E.S. and A.K.; methodology, Y.E.S., A.K. and M.J.; software, Y.E.S.; validation, Y.E.S., M.J., S.B. and G.A.; formal analysis, Y.E.S. and A.K.; investigation, Y.E.S. and M.J.; resources, A.K., S.B. and G.A.; data curation, Y.E.S.; writing—original draft preparation, Y.E.S. and M.J.; writing—review and editing, A.K., S.B. and G.A.; visualization, Y.E.S. and M.J.; supervision, A.K.; project administration, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Health Institutes of Türkiye (TÜSEB), grant number 33987, and Kocaeli University Scientific Research Projects Coordination Unit, grant number 2024/3760.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: We have uploaded the implementation code on our public GitHub (a cloud-based web platform used by developers to store, manage, and collaborate on code projects) repository, which can be accessed using this link: https://github.com/EymenSezen/EVMobile, (accessed on 25 May 2026).

Acknowledgments: The authors acknowledge the support of the Health Institutes of Türkiye and the Kocaeli University Scientific Research Projects Coordination Unit.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
CSMF	Charging Station Recommendation Algorithm using Mean Field Theory
LLM	Large Language Model
MARL	Multi-Agent Reinforcement Learning
CTDE	Centralized Training and Decentralized Execution
XAI	Explainable Artificial Intelligence
EMRA	Energy Market Regulatory Authority of Türkiye
AFR	Available Facility Rate
AMD	Average Minimum Distance
RT	Response Time
MCWT	Mean Charging Waiting Time
CFR	Charging Failure Rate
API	Application Programming Interface
SoC	State of Charge
ETA	Estimated Time of Arrival
ITSs	Intelligent Transportation Systems

References

1. Bayani, R.; Soofi, A.F.; Waseem, M.; Manshadi, S.D. Impact of Transportation Electrification on the Electricity Grid—A Review. *Vehicles* **2022**, *4*, 1042–1079. [CrossRef]
2. Kumar, R.; Kanwal, A.; Asim, M.; Pervez, M.; Mujtaba, M.; Fouad, Y.; Kalam, M. Transforming the transportation sector: Mitigating greenhouse gas emissions through electric vehicles (EVs) and exploring sustainable pathways. *AIP Adv.* **2024**, *14*, 035320. [CrossRef]
3. Rigogiannis, N.; Bogatsis, I.; Pechlivanis, C.; Kyritsis, A.; Papanikolaou, N. Moving towards Greener Road Transportation: A Review. *Clean Technol.* **2023**, *5*, 766–790. [CrossRef]
4. MacCarley, C.A. Electric vehicles. In *Non-Petroleum Automotive Transportation*; Springer: Cham, Switzerland, 2025; pp. 391–572.
5. Huang, Y.; Ren, H.; Liu, Z.; Chen, D. A Hierarchical Spatio-Temporal Framework for Sustainable and Equitable EV Charging Station Location Optimization: A Case Study of Wuhan. *Sustainability* **2026**, *18*, 497. [CrossRef]
6. Çelik, S.; Ok, Ş. Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning. *Heliyon* **2024**, *10*, e29153. [CrossRef] [PubMed]
7. Lundberg, H. Increasing the Trustworthiness of AI-Based In-Vehicle IDS Using eXplainable AI. Master's Thesis, Mid Sweden University, Sundsvall, Sweden, 2022.
8. Shanmugam, P.K.; Thomas, P. Optimization strategies for electric vehicle charging and routing: A comprehensive review. *Gazi Univ. J. Sci.* **2024**, *37*, 1256–1285. [CrossRef]
9. Khan, M.O.; Kirmani, S.; Rihan, M. A comprehensive review of methodologies for the optimal allocation of electric vehicle charging stations alongside distributed generation. *Smart Sci.* **2025**, *13*, 264–293. [CrossRef]
10. Kiasari, M.; Aly, H. Agentic Artificial Intelligence for Smart Grids: A Comprehensive Review of Autonomous, Safe, and Explainable Control Frameworks. *Energies* **2026**, *19*, 617. [CrossRef]
11. Michailidis, P.; Michailidis, I.; Kosmatopoulos, E. Reinforcement Learning for Electric Vehicle Charging Management: Theory and Applications. *Energies* **2025**, *18*, 5225. [CrossRef]

12. Zhang, W.; Liu, H.; Wang, F.; Xu, T.; Xin, H.; Dou, D.; Xiong, H. Intelligent electric vehicle charging recommendation based on multi-agent reinforcement learning. In *Proceedings of the Web Conference 2021 (WWW '21), Ljubljana, Slovenia, 19–23 April 2021*; Association for Computing Machinery: New York, NY, USA, 2021; pp. 1856–1867.
13. Cui, K.; Zhu, Y.; Chang, Y.; Qin, J.; Li, Z. Charging station recommendation based on mean field multi-agent reinforcement learning. *Int. Core J. Eng.* **2023**, *9*, 240–250.
14. Peng, J.; Ren, T.; Chen, Z.; Chen, W.; Wu, C.; Ma, C. Efficient training for energy management in fuel cell hybrid electric vehicles: An imitation learning-embedded deep reinforcement learning framework. *J. Clean. Prod.* **2024**, *447*, 141360. [CrossRef]
15. Sapkota, Y. Poisson Distribution Based Algorithm to Reduce Grid Harmonics Caused by EV Chargers. Ph.D. Thesis, Ontario Tech University, Oshawa, ON, Canada, 2023.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.