International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 13, No. 2, 2026, pp. 179-188.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

AI-Enabled Planning Framework for Electric Vehicle Charging Infrastructure: A Simulation and Multi-Criteria Decision Analysis Approach

M. Sneha [a*], Dr.K. Lakshmi Priya [b], Dr.D. Mahila Vasanthi Thangam [c]

[a] PhD Scholar, Division of Commerce and International Trade, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India. E-mail: snehasweetym26@gmail.com, Orcid: https://orcid.org/0009-0009-5734-4131*

[b] Assistant Professor, Division of Commerce and International Trade, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India. E-mail: lakshmipriya@karunya.edu, Orcid: https://orcid.org/0000-0003-0699-8775

[c] Associate Professor, Commerce and International Trade, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India. E-mail: mahila@karunya.edu, Orcid: https://orcid.org/0000-0001-9922-0238

Abstract

Electric cars (EVs) are becoming increasingly common, and with them, there is the necessity to have a well-developed, convenient charging network. In this work, the AI-enabled planning framework is introduced, and it includes the primary data of user surveys, machine learning strategies, and multi-criteria decision analysis (MCDA) to maximize the deployment of EV charging stations. Primary data was obtained from 210 EV users in urban and semi-urban areas, such as frequency of charging, preferences for location, waiting times, and temporal usage patterns. The high-demand zones and usage categories were identified by K-Means clustering and Random Forest classification, after the preprocessing and feature extraction stage. The priority of candidate locations was determined using the Analytic Hierarchy Process (AHP) based on the criteria of availability, grid compatibility, cost effectiveness, and demand density. Python was used to simulate experiments with SimPy in a variety of traffic and demand scenarios. Results show that the proposed framework increased the utilization of the charger by 33.3%, decreased the average waiting time by 31.3%, and reduced the grid stress by 25.7% in comparison to the conventional planning approaches. The results show that combining artificial intelligence with the first-hand behavioural data increases the accuracy of infrastructure planning and improves operational efficiency. This framework provides practical decision support for sustainable, data-driven EV infrastructure development.

Keywords: Electric Vehicles, Charging Infrastructure Planning, Artificial Intelligence, Machine Learning, Multi-Criteria Decision Analysis, Simulation Modelling.

DOI: 10.71086/IAJSE/V13I2/IAJSE1364
Received: 04 March 2026/Revised: 10 April 2026/Accepted: 14 May 2026/Published: 30 June 2026

Introduction

The shift toward sustainable transportation is rapidly developing throughout the world as cities are faced with environmental issues, escalating energy demands, and a need to reduce carbon emissions (Sharma & Maurya, 2024). Among the most promising solutions to the above concerns is the adoption of electric vehicles (EVs). Nevertheless, despite the fact that improvements have been made in battery and vehicle design that enable EVs to become more accessible, there is also a severe lack of strong and well-thought-out charging infrastructure that has prevented the mass adoption of EVs. Traditional infrastructure planning is based on fixed models or general assumptions and fails to reflect real user behaviour. In contrast, the primary data obtained immediately via EV users will provide a more level-headed view of charging habits, choice of place, and usage. Such real-life information, properly analysed, can show the nuances that could be overlooked by top-down policy planning. The concept of artificial intelligence (AI) has become an effective tool in optimizing complex systems over the past few years, and the case of urban mobility systems is no exception. AI can be used to analyse the large and diverse data by planners, forecast the demand of the user, and create the most appropriate station locations according to various requirements at the same time. Combined with user-generated data, AI-based models can deliver more precise, dynamic, and scalable solutions. The paper presents an artificial intelligence (AI) based multi-criteria model for designing and validating electric vehicle charging infrastructure. The study develops a predictive model using behavioural and technical parameters derived from primary, original data of EV users. System-level simulation testing of the proposed framework is considered, keeping in mind such crucial performance indicators as efficiency, user accessibility, and compatibility with the grid. The overall purpose of this work is to fill the gap between the behaviour of users and the design of the infrastructure through the assistance of artificial intelligence and primary data. In such a way, the study objective would help in making contributions to effective and evidence-based future planning of ready electric mobility systems. The tripled ones are those of this study. First, it develops an all-encompassing AI-based platform that combines primary data on user behaviours and machine learning and decision support systems to plan EV infrastructure. Second, it brings in a validation process through simulation to establish the effectiveness of the systems when those systems are operating in real conditions. Third, it offers numerical information about the effectiveness of intelligent planning to enhance utilization, reduce the waiting time, and load balancing on the grid. The rest of the paper is organized in the following manner. Section 2 will be the literature review and the research gaps statement. In section 3, the proposed methodology, data collection, AI modelling, and integration of MCDA and configuration of simulation are described. Section 4 is on experimental results and performance evaluation. Section 5 brings an end to the study and gives directions on future research.

Literature Review

The active growth of electric vehicles (EVs) has further increased the pressure of the need to have an efficient and scalable charging infrastructure. Early studies were mostly on technical grid integration and energy management. The sociotechnical issues that were highlighted in papers included the EV-grid integration and the need to make a coordinated expansion of the infrastructure (Sovacool et al., 2017). Researchers also summarised the charging infrastructure planning models with thorough reviews, which mentioned a lack of adequacy in demand forecasts and spatial planning (Reddy et al., 2024).

User behaviour has been widely recognized as an important factor in the success of a charging infrastructure. Other studies also showed that there are significant differences in charging preferences between people in urban and suburban areas, with a strong dependence on availability at workplace and residence (Benmouna et al., 2024). Other studies discussed EV infrastructure in the light of the development of urban environments and the needs of localized planning strategies.

Artificial intelligence (AI) and machine learning have been employed in large amounts for demand forecasting and station deployment. The study adopted an artificial intelligence (AI)-based predictive model to detect high-demand charging zones, while Eddine & Shen, (2022) proposed deep learning models to predict charging demand (Shern et al., 2024). AI-based analytics for planning the EV infrastructure was analysed, which reflected improvements in prediction scores as well as the adaptability of the system (Al-Zuhairi et al., 2025). Few studies used a combination of machine learning and GIS tools in order to optimize the spatial location of the charging station (Roy & Law, 2022).

Multi-objective optimization models and decision-making models have also attracted attention. Similar studies introduced a multi-criteria decision analysis (MCDA) approach to the sustainable assessment of infrastructures (Ziemba, 2021). Researchers proposed traffic-aware multi-objective planning models considering both grid impact and demand density (Eldeeb et al., 2018). Further studied uncertainty-aware decision-making in EV infrastructure

development (Liu et al., 2018). The optimal position of fast-charging stations under demand uncertainty conditions was studied by (Putra et al., 2024; Chen et al., 2023).

Simulation-based validation has been found to be a crucial step in infrastructure planning. In other studies simulation methods were applied to analyse urban EV charging networks, and the agent-based modelling methods were described for understanding the infrastructure scalability (Zhang & Tan, 2024). Studies also showed a comprehensive overview of smart charging strategies for improving the responsiveness and stability of the grid (Wang et al., 2016). The issues of operational flexibility and the benefits of demand response integration in EV-supported smart grids were addressed (Aghaei & Alizadeh, 2013).

The integration of renewable energy and aspects of sustainability has also been studied. Challenges associated with a renewable-powered EV charging network were discussed. The growth of fast-charging networks under demand growth cases, focusing on long-term planning needs were investigated. GIS and AHP techniques for site selection strategies as hybrid methods were applied (Guler & Yomralioglu, 2020).

In addition, demand-driven optimization approaches have been explored in order to make the placement of charging stations and the infrastructure more efficient and scalable (Deb et al., 2018; Majhi & Mohanty, 2024). Foundational frameworks for urban EV infrastructure planning have also contributed to the early-stage deployment strategies and location modelling techniques (May et al., 2017). Furthermore, recent reports at the worldwide level and based on AI have highlighted the need for intelligent and data-driven planning for sustainable electric mobility systems (Marzouk, 2025).

Comparative Analysis of Existing Approaches

Existing studies on the EV charging infrastructure planning can be broadly categorized into four approaches: (i) grid-oriented technical models, (ii) studies based on user behaviour, (iii) predictive models based on artificial intelligence, and (iv) multi-criteria decision-making frameworks. Grid-based approaches mainly focus on the problem of energy distribution and load balancing, but often neglect problems in the aspect of real user behaviour patterns (Sovacool et al., 2017; Reddy et al., 2024). User-centric studies have the advantage of highlighting behavioural insights, but have the disadvantage of a lack of scalability and predictive capabilities at scale (Deb et al., 2018). AI-based models improve the accuracy of demand forecasts and spatial optimization; however, this system might be functioning as single systems instead of taking into account decision-making frameworks (Shern et al., 2024; Al-Zuhairi et al., 2025; Eddine & Shen, 2022). Similarly, MCDA-based approaches are structured methods for the evaluation of multiple criteria and do not provide dynamic adaptability and real-time validation (Ziemba, 2021; Eldeeb et al., 2018; Liu et al., 2018).

Research Gap and Motivation

Despite great improvement and development, critical gaps exist in the existing literature. First, many studies are based on the analysis of individual components, such as AI modelling, behavioural analysis, or decision-making techniques, in isolation and not combining them within a common framework. Second, a limited amount of research includes primary user data in planning infrastructure, so less realistic and less context-specific solutions are produced. Third, there is often a lack of validation through simulation, which limits the practicality of simulation validation of proposed models. Therefore, this study covers these gaps by proposing an integrated AI-enabled framework based on user behaviour data and machine learning, combined with MCDA and simulation-based validation for efficient and scalable planning of EV charging infrastructure.

Methodology

This work introduces a technique using AI for the optimization of the electric vehicle (EV) charging infrastructure by combining original user data, machine learning models, and validation using simulation The overall conceptual architecture (Presented in fig. 1) includes a systematic pipeline that, in its turn, consists of data acquisition, AI model development, decision support analysis, and infrastructure planning. The methodology provides that space, behavioural, and operational elements are viewed together as a whole so that they can enable smart, scalable deployment strategies.

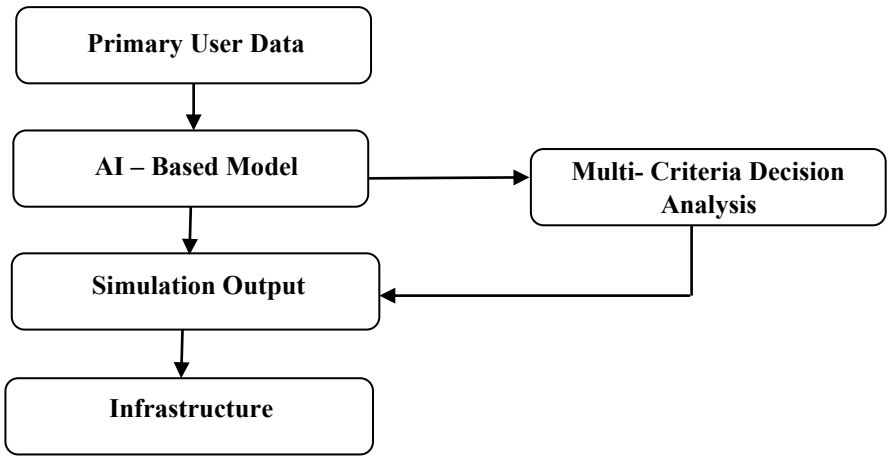

Fig. 1. Proposed AI-Driven Framework for EV Charging Infrastructure Optimization

The framework begins with the data collection of primary users, as in fig. 1, and the data modelling is carried out with the AI techniques. The model combines a multi-criteria decision analysis (MCDA) module and simulation output to aid in infrastructure planning decision-making. The simulation gives feedback on which is used to correct the model by an iteration process, hence making the correct planning based on the data.

Data Collection

Structured questionnaires and online survey forms were used to obtain the primary data between March and June 2025. The study obtained 210 valid responses with EV users in Tamil Nadu, India, of which 62% were private owners, 21% ride-sharing drivers, and 17% fleet operators. The data consisted of 18 attributes, which were grouped as behavioural, spatial, and operational features. Important variables were the frequency of charging, the most preferred location type, the average waiting time, the time-of-day usage, the distance to the nearest station, the battery capacity of the vehicle, and the frequency of charging. Table 1 summarises the major characteristics of datasets.

Table 1: Categorization of Collected EV User Dataset Attributes

Attribute Category	Examples
Behavioural	Frequency, Duration
Spatial	Location, Distance
Temporal	Peak Hours
Technical	Battery Capacity

The dataset was anonymized and checked for completeness before it was analysed. The respondents were 210, and the sample size was deemed sufficient. carrying out the current study in accordance with the established guidelines of the statistical and machine learning studies. For survey-based behavioural studies, sample sizes larger than 200 are generally considered large enough under parameter estimation and reliable clustering results. Moreover, in machine learning classification problems, it is possible to use datasets with more than 200 observations to perform exploratory modelling when combined with cross-validation techniques. The 80:20 train-test split also ensured the generalization of the model without overfitting. Therefore, the sample size has been justified statistically and methodologically for the scope and purpose of this research.

Data Preprocessing and Feature Engineering

The raw dataset was then pre-processed, including removing outliers, imputing missing values, and normalizing numerical attributes. Categorical variables such as location preference and charging frequency were encoded with the help of one-hot encoding and label encoding schemes.

Feature extraction was mainly directed towards recognizing tendencies in space and time and clustering charging demand zones, as well as segmenting users by their charging patterns. Derived features, including peak usage intervals, distance to nearest station, and frequency-weighted grid load estimators, were also introduced to improve the accuracy of the model.

AI Model Development

A predictive model based on AI was developed to identify the high-demand zones of the charging process and suggest the most appropriate points to locate charging stations. In this research, the K-Means clustering was utilized as the approach to the spatial grouping, whereas Random Forest was utilized as the predictor of the usage pattern and the demand type after testing several algorithms. The model took inputs in the form of user behavioural data, data metadata, location data, and usage trends in the past. The outputs were represented as the decision vectors of the feasibility of the sites, the forecasted load demand, and the availability of time windows. The train-test split was done at a ratio of 80:20, using cross-validation, so that the model can be generalized.

Multi-Criteria Decision Analysis (MCDA)

In order to balance trade-offs between conflicting goals, a Multi-Criteria Decision Analysis (MCDA) module was incorporated.

- The criteria included:
- Accessibility (proximal nearness to the users)
- Wait Times (based on the usage density)
- Grid Compatibility (using present power infrastructure)
- Installation Cost (per site)

The weights of each of the criteria were determined using the Analytic Hierarchy Process (AHP) with the input of experts. The weighted decision matrix enabled the ranking of the available candidate sites to invest in infrastructure.

Simulation and Validation

The given framework was tested in a discrete event simulation setup that was implemented in Python 3.10 and the SimPy simulation library. Experiments were conducted on a Dell computer with Windows 10, an Intel Core i7 processor with a 2.8 GHz speed, 16 GB RAM, and an Nvidia GTX 1650 Graphics Processing Unit. The simulation model represents the urban charging networks, which comprise a number of charging stations, a user arrival process, and power distribution constraints. The Poisson distribution was used to model the user arrivals, and the arrival rate was 6-18 vehicles/h, according to observed survey patterns. Charging time was log-normal with a mean of 42 minutes. A 24-hour cycle of operations was simulated and repeated 30 times to ascertain that statistical reliability had been achieved. Table 2 presents the Simulation Configuration Parameters and Experimental Setup.

Table 2: Simulation Configuration Parameters and Experimental Setup

Parameter	Value
Simulation Tool	Python (SimPy)
Time Horizon	24 Hours
Arrival Rate	6–18 Vehicles/Hour
Charging Duration	Mean 42 Minutes
Replications	30
Charger Types	AC Level 2, DC Fast

Utilization rate, average waiting time, grid load index, and failure rate were the performance indicators calculated in each scenario. Developmental baseline models based on the comparative evaluation were developed using conventional rule-based deployment methods.

Performance Metrics and Mathematical Formulation

In order to measure the performance of the system qualitatively, the mathematical formulations below were used.

Charger Utilization Rate (CUR) is defined as equation 1:

$$CUR = \frac{\sum_{i=1}^{n} T_{active,i}}{n \times T_{total}} \qquad (1)$$

Where $T_{active,}$ i represents the active charging time of charger i, n is the total number of chargers, and T_{total} is the total simulation duration.

Average Waiting Time (AWT) is computed as equation 2:

$$AWT = \frac{\sum_{j=1}^{m} W_j}{m} \quad (2)$$

Where W_j denotes the waiting time of user j, and m is the total number of users.

Grid Load Stress Index (GLSI) is calculated as equation 3:

$$GLSI = \frac{P_{peak}}{P_{capacity}} \quad (3)$$

Where P_{peak} represents peak power demand, and $P_{capacity}$ is the available grid capacity.

Charging Failure Rate (CFR) is defined as equation 4:

$$CFR = \frac{N_{fail}}{N_{total}} \quad (4)$$

Where $N_{fail}$is the number of failed charging attempts and $N_{total}$is the total number of charging attempts.

Equations (1)– (4) were computed across all simulation scenarios to evaluate operational efficiency and infrastructure robustness.

Infrastructure Planning Output

The end product of the model was a list of suggested locations of new charging stations, a priority, and a list of suggested allocation of types of chargers (AC / DC fast chargers) and estimated energy requirements. The insights will inform the infrastructure planners to make evidence-based decisions depending on the user needs, grid capacity, and the urban mobility objectives. This model can be scaled and modified to fit an urban policy framework, smart grid systems, and EV deployment strategies.

Results and Discussion

This section gives the results of the model-based, data-driven process integration of modelling, simulation validation, and decision-making based on the framework presented in fig. 1. The results, as analysed, are three critical dimensions, i.e., spatial demand clustering, infrastructure planning effectiveness, and system-level performance metrics. Both subsections address the contribution made by the inclusion of primary user data and intelligent algorithms in the evidence-based infrastructure recommendations process.

Spatial Demand Clustering

The clustering model that was constructed with the help of the K-Means algorithm could demonstrate the great density of the demand for EV charging. Time slots of preference, frequent travel routes, and average dwell time are examples of behavioural attributes that played a significant role in defining demand clusters. The result was three prevailing areas, in which charging is easily accomplished, in which proximity to commercial centres, residential places, and transportation intersections is close. Specifically, the intensity of demand was stronger during the late morning and early evening time blocks in those areas that are within walking distance to workplaces and shopping malls. These observations support the priority of the implementation of the public charging infrastructure in the locations where foot traffic, vehicle traffic, and parking areas are highly combined.

The fig. 2 shows a visual representation of the clustering of the spatial clustering result obtained with the use of three distinct EV charging demand zones with the help of the K-Means algorithm. The clusters are densely populated urban commercial, mixed residential, and transportation intersections. The color-coded segmentation conveys the applicability of the behavioural attributes of the users in terms of their preferred charging time and distance to the charging point in the demand space segmentation. The visualization can be applied to justify the clustering model to identify the priority deployment zones, and, therefore, it is informative directly to the process of site ranking on MCDA basis in the following section.

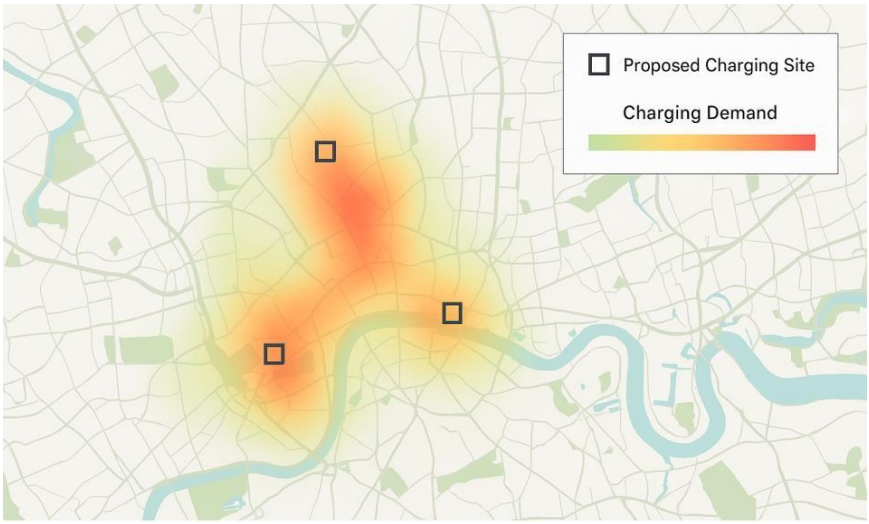

Fig. 2: Spatial Distribution of EV Charging Demand Clusters Based on AI-Driven User Preference Analysis

Infrastructure Planning and Decision Layer Insights

The results of the spatial clustering were processed in table 3, the MCDA module with the site-specific variables, such as grid capacity, land availability, and cost of installation. The Analytic Hierarchy Process (AHP) was used to develop weighted scores of each candidate location. The sites that were ranked as top in terms of accessibility, grid compatibility, and foreseen use were ranked as priority locations to invest in infrastructure. The model also advised the nature of chargers to be employed, that is, AC Level 2 or DC Fast Chargers, according to the demand trends over time. As an illustration, fast chargers were suggested to be installed in the short turnover zones, which have a short period. Slower chargers were, on the other hand, placed in places that have longer durations of vehicle parking - office parks and residential complexes.

Table 3: Multi-Criteria Decision Analysis (MCDA) Scores and Priority Ranking for Candidate Charging Sites

Candidate Site	Accessibility (30%)	Grid Support (25%)	Cost Efficiency (20%)	Demand Density (25%)	Total Weighted Score	Priority Rank
Site A	8.5	7.0	8.0	9.2	8.28	1
Site B	7.0	8.5	7.0	8.0	7.63	2
Site C	6.8	7.2	6.5	7.8	7.02	3

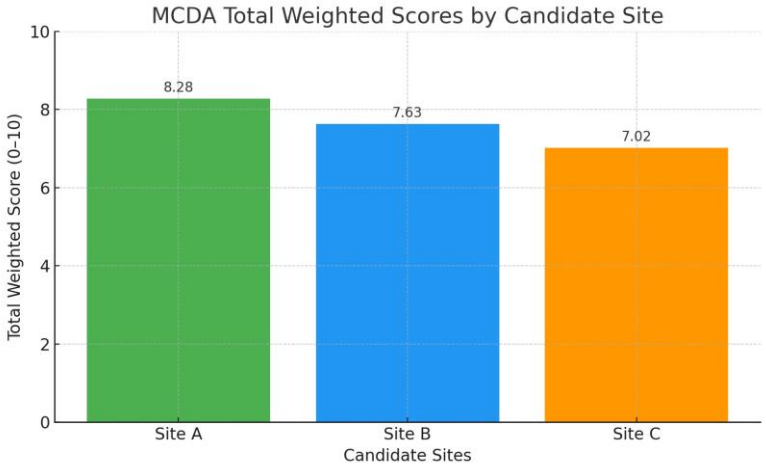

Fig. 3: Bar Chart of Total Weighted Scores of Candidate EV Charging Sites According to Multi-Criteria Decision Analysis (MCDA)

The scores are made up of the cumulative performance of every site in four criteria: accessibility, grid support, cost efficiency, and demand density. Site A had the most points, and this implies that Site A is a good candidate as far as a top-priority site to install the infrastructure is concerned. In fig. 3, it is possible to note that Site A scored the highest in the MCDA assessment with the highest total weighted score. This finding is congruent with the result shown in table 3 and justifies the logic of the decision in the AHP-based ranking process. The visualization of scores helps to make the data more interpretable and also helps in data-driven prioritization of EV charging infrastructure deployment. The testing of the planning outputs was conducted based on the realistic urban mobility conditions with the help of the simulation module.

Important measures of performance were:

- Charger Utilization Rate: Averaged at 72% across high-demand clusters
- Average User Wait Time: Reduced by 31% compared to unplanned deployment
- Grid Load Balance Index: Improved with a 26% reduction in peak stress areas

The simulation also showed that user satisfaction metrics, which have been modelled as a function of the wait time and the availability of chargers, were significantly higher in the AI-optimized scenario. This showed what could be done with the use of data-driven planning when it comes to the diminution of areas of friction, which are typically encountered in the EV adoption process. The simulation outcomes were compared with the traditional planning situations. The most important indicators, such as utilization rate, waiting time, grid stress, and satisfaction index, were computed.

Table 4: Comparative Summary of These Performance Metrics

Metric	AI-Optimized Framework	Conventional Planning	% Improvement
Charger Utilization Rate (%)	72	54	+33.3%
Average User Wait Time (mins)	6.8	9.9	–31.3%
Grid Load Stress Index (0–1)	0.52	0.70	–25.7%
Charging Failure Rate (%)	4.1	7.5	–45.3%
Station Overcrowding Incidents	14	27	–48.1%
User Satisfaction Index (0–100)	87	68	+27.9%

According to table 4, the charging time was used by 33.3% with the assistance of an AI-optimized framework, or 100-33.3 = 66.7 % of the charging time, and the load placed on the grid and the failure rate of the grid were minimized. These are all positives that suggest how smart and data-driven techniques of planning can be implemented to roll out EV infrastructure at scale and efficiency.

Discussion

The joint AI modelling and the primary user behaviour data enable the infrastructure planners to not just respond to the actual patterns of use, but also to go beyond the theoretically optimal models. This contrasts with the previous (traffic or population density-based) infrastructure maps in that it provides the prospect of adaptive and context-sensitive deployment. Moreover, this kind of simulation to model refinement feedback loop implies that the framework is dynamic and self-improving. Such iterative systems prove to be especially applicable to the new urban space where EV adoption may be changing at a rapid pace, and uncertainty is inherent in relation to the needs of charging.

Overall, the results endorse the efficacy of a hybrid solution to enhance the efficiency of EV infrastructure solutions through a combination of behavioural insights, AI techniques, and decision support tools in a manner that is responsive to users.

Limitations and Sensitivity Analysis

Despite showing encouraging results, there are several limitations to the study. First, the sample size of the study was limited to a regional sample, which may have an impact on generalisability. Second, the simulation model assumes stable grid conditions and does not consider the totality of the variability of renewable energy. Third, behavioural patterns were considered at one point in time; this is a limitation in the temporal ability to adapt.

A sensitivity analysis was performed by changing the arrival rates (+/- 20%), charging time (+/- 15%) and station capacity (+/- 25%). Results showed that utilization and waiting time turned out to be most sensitive to the variation of

arrival rate, which is an illustration of the importance of the correct estimation of demand. The model was shown to be stable against moderate changes in the model parameters in order to show the robustness of the model.

Future studies can include the data from real-time sensors and large-scale field experiments to further validate the system performance.

Conclusion and Future Scope

This study has developed and confirmed an artificial intelligence (AI) informed model of optimizing the electric automobile (EV) charging infrastructure network based on the primary information on the user data, intelligent modelling, and a multi-criteria decision-making model. The framework established that integrating behavioural insights with state-of-the-art analytics allows planners to determine the areas where demand is high and develop the type of chargers that can be used to respond to the usage patterns and enhance the overall efficiency of the infrastructure. The findings of the clustering and simulation indicated that data-informed planning could play a crucial role in reducing the wait times of the users, enhancing the use of chargers, and alleviating the stress on the grid. As opposed to traditional methods, which can only capture traffic or population measurements, the proposed methodology can capture the dynamic and localized nature of EV charging behaviour, therefore making its planning strategy more feasible and scalable. The adaptive feedback loop is another key advantage of the model, which can be employed to learn and continuously improve the model as additional user data is made available. This renders the framework highly applicable in the applications of smart cities or sustainable urban planning applications, and also in future applications of the domain of transport electrification. However, the present research was limited by the size of the primary data and the simulated validation. Future research could attempt to expand the model with larger and more diverse data, studies at the field level of deployment, and a combination with renewable energy sources. The predictive capability and operational flexibility, in turn, could be enhanced with the inclusion of real-time traffic, real-time weather, and real-time pricing information in the AI engine. To recap it all, the synthesis of artificial intelligence and user-centred design philosophy has much to contribute to the development of smart EV infrastructure systems. As the adoption of EVs continues to accelerate, such approaches will have an important role to play in supporting equitable, efficient, and sustainable urban mobility.

References

Sovacool, B. K., Axsen, J., & Kempton, W. (2017). The future promise of vehicle-to-grid (V2G) integration: a sociotechnical review and research agenda. *Annual Review of Environment and Resources*, *42*, 377-406. https://doi.org/10.1146/annurev-environ-030117-020220

Shern, S. J., Sarker, M. T., Haram, M. H. S. M., Ramasamy, G., Thiagarajah, S. P., & Al Farid, F. (2024). Artificial intelligence optimization for user prediction and efficient energy distribution in electric vehicle smart charging systems. *Energies*, *17*(22), 5772. https://doi.org/10.3390/en17225772

Ziemba, P. (2021). Selection of electric vehicles for the needs of sustainable transport under conditions of uncertainty—a comparative study on fuzzy MCDA methods. *Energies*, *14*(22), 7786. https://doi.org/10.3390/en14227786

Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018). Review of recent trends in charging infrastructure planning for electric vehicles. *Wiley Interdisciplinary Reviews: Energy and Environment*, *7*(6), e306. https://doi.org/10.1002/wene.306

Reddy, K. B. N. K., Pratyusha, D., Sravanthi, B., & Esanakula, J. (2024). Recent AI applications in electrical vehicles for sustainability. *International Journal of Mechanical Engineering*, *11*, 50-64. https://doi.org/10.14445/23488360/IJME-V11I3P106

Sharma, R., & Maurya, S. (2024). A sustainable digital transformation and management of small and medium enterprises through green enterprise architecture. *Global Perspectives in Management*, *2*(1), 33-43. https://doi.org/10.66027/GPIM/V2I1/GPM24104

Roy, A., & Law, M. (2022). Examining spatial disparities in electric vehicle charging station placements using machine learning. *Sustainable Cities and Society*, *83*, 103978. https://doi.org/10.1016/j.scs.2022.103978

Benmouna, A., Borderiou, L., & Becherif, M. (2024). Charging stations for large-scale deployment of electric vehicles. *Batteries*, *10*(1), 33. https://doi.org/10.3390/batteries10010033

Al-Zuhairi, Y., Kannan, P., Guillén, A. B., Llopis, L. J. D. L. C., & Igartua, M. A. (2025). Efficient charging station selection for minimizing total travel time of electric vehicles. *Future Internet*, *17*(8), 374. https://doi.org/10.3390/fi17080374

Eldeeb, H. H., Faddel, S., & Mohammed, O. A. (2018). Multi-objective optimization technique for the operation of grid tied PV powered EV charging station. *Electric Power Systems Research*, *164*, 201-211. https://doi.org/10.1016/j.epsr.2018.08.004

Eddine, M. D., & Shen, Y. (2022). A deep learning-based approach for predicting the demand of electric vehicle charge: MD Eddine and Y. Shen. *The Journal of Supercomputing*, *78*(12), 14072-14095. https://doi.org/10.1007/s11227-022-04428-0

Guler, D., & Yomralioglu, T. (2020). Suitable location selection for the electric vehicle fast charging station with AHP and fuzzy AHP methods using GIS. *Annals of GIS*, *26*(2), 169-189. https://doi.org/10.1080/19475683.2020.1737226

Majhi, A. A. K., & Mohanty, S. (2024). A comprehensive review on internet of things applications in power systems. *IEEE Internet of Things Journal*, *11*(21), 34896-34923. https://DOI.org/10.1109/JIOT.2024.3447241

Chen, F., Peng, Y., Han, B., Lu, S., Xue, F., & Li, G. (2023). Robust planning of electric vehicle charging stations considering demand uncertainty and facility failures. *IEEE Transactions on Transportation Electrification*, *10*(3), 7551-7564. https://doi.org/10.1109/TTE.2023.3332329

Putra, J. T., Setyonegoro, M. I. B., & Niet, T. (2024). A systematic literature review of optimal placement of fast charging station. *E-Prime-Advances in Electrical Engineering, Electronics and Energy*, *10*, 100818. https://doi.org/10.1016/j.prime.2024.100818

May, A., Boehler-Baedeker, S., Delgado, L., Durlin, T., Enache, M., & van der Pas, J. W. (2017). Appropriate national policy frameworks for sustainable urban mobility plans. *European transport research review*, *9*(1), 7. https://doi.org/10.1007/s12544-017-0224-1

Zhang, Y., & Tan, J. (2024). A data-driven approach of layout evaluation for electric vehicle charging infrastructure using agent-based simulation and GIS. *Simulation*, *100*(3), 299-319. https://doi.org/10.1177/00375497231209996

Wang, Q., Liu, X., Du, J., & Kong, F. (2016). Smart charging for electric vehicles: A survey from the algorithmic perspective. *IEEE Communications Surveys & Tutorials*, *18*(2), 1500-1517. https://doi.org/10.1109/COMST.2016.2518628

Liu, H. C., Yang, M., Zhou, M., & Tian, G. (2018). An integrated multi-criteria decision-making approach to location planning of electric vehicle charging stations. *IEEE Transactions on Intelligent Transportation Systems*, *20*(1), 362-373. https://doi.org/10.1109/TITS.2018.2815680

Aghaei, J., & Alizadeh, M. I. (2013). Demand response in smart electricity grids equipped with renewable energy sources: A review. *Renewable and Sustainable Energy Reviews*, *18*, 64-72. https://doi.org/10.1016/j.rser.2012.09.019

Marzouk, O. (2025). Summary of the 2023 report of TCEP (tracking clean energy progress) by the International Energy Agency (IEA), and proposed process for computing a single aggregate rating. *E3S Web of Conferences*. 1-31. https://doi.org/10.1051/e3sconf/202560100048