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AI-Enabled Solutions to Challenges in Electric Vehicle Charging Infrastructure in Pakistan: A Systematic Review

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ABSTRACT

Pakistan has set a target of achieving 30% electric vehicle (EV) penetration by 2030; however, limited and inefficient Electric Vehicle Charging Infrastructure (EVCI) remains a critical barrier to this transition. This study investigates the key technical, financial, regulatory, and social challenges hindering EVCI deployment in Pakistan through a Systematic Literature Review (SLR) of 55 peer-reviewed studies published between 2008 and 2024 from databases such as Google Scholar, IEEE Xplore, ScienceDirect, and Mendeley using a PDCP framework, complemented by a focus group study involving nine experts (n = 9) from academia, industry, and policy sectors. The SLR scope covers publications related to EV infrastructure planning, grid integration, policy frameworks, and AI-enabled optimization to identify key challenges and solution pathways. Ten critical challenges were identified, including insufficient charging stations, high upfront costs, grid instability, range anxiety, battery supply constraints, policy uncertainty, and workforce limitations. In order to overcome these obstacles, the paper suggests AI-based solutions that combine machine learning, reinforcement learning, digital twins, predictive analytics, and dynamic pricing. Such tools assist in the optimal location of charging stations, load forecasting, subsidy targeting, grid stability, and battery life cycle management under Pakistan's National Electric Vehicle Policy (NEVP) 2019 and New Energy Vehicles Policy 2025-30. The results suggest that combining policy reforms with AI-driven decision-making can speed up scalable, resilient, and sustainable EVCI development, rebranding Pakistan's EV transition into a data-driven and adaptive national strategy towards its 2030 climate objectives.

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1. Introduction

The reduction of the global temperature to 1.5°C is a key climate goal and focus of the International Energy Agency (IEA). In the spirit of international commitments, Pakistan has targeted about 60% of its power production through renewable and alternative sources of energy by 2030, such as hydropower, in its National Climate Change Policy (MoCC, 2021). However, this transition remains structurally slow because of grid limitations, fuel reliance, infrastructure complexity, and current policies governing the renewable market. Simultaneously, the quality of air in urban areas is getting worse; Lahore is often rated as one of the most polluted cities globally. Thus, the need to electrify mobility is urgent as the transport sector is a significant source of greenhouse gas (GHG) and particulate pollution.

To solve this problem, the Government of Pakistan (GoP) established a goal of EV sales penetration of 30% by 2030 and launched the National Electric Vehicle Policy (NEVP) in 2019, with revisions introduced in the New Energy Vehicles Policy 2025-30. One of the key facilitators of this shift is the creation of Electric Vehicle Charging Infrastructure (EVCI).

There is an increasing number of peer-reviewed sources that have explored the topic of EVCI planning, grid integration, and sustainable transport systems, which gives this study a solid academic basis to analyze. According to the authors of Pandey (2024); Prajapati et al. (2025), some of the challenges that EV infrastructure development encounters are grid constraints, charging optimization, and integration of renewable resources. Recent research underlines the importance of Artificial Intelligence (AI) in improving charging operations, increasing the efficiency of energy, and making the grid more stable (Yang et al., 2025). AI-powered models allow smart demand forecasting, load balancing, and infrastructure planning, which is essential to the sustainable growth of EV ecosystems (Mosavi et al., 2019; Pandey, 2024).

Moreover, the incorporation of renewable energy in EV charging contributes to the evolution of sustainable transport through the decrease of GHG emissions and use of fossil fuels (Prajapati et al., 2025; Sovacool et al., 2017). Additionally, smart grid and vehicle-to-grid (V2G) allows bidirectional energy flow, which makes the grid more stable and ensures higher penetration of renewable energy sources (Fang et al., 2012; Lund, 2015).

Solar-integrated EV charging facilities play an important role in the decarbonization process, where researchers have reported a significant decrease in lifecycle emissions and operational carbon footprints (Prajapati et al., 2025). In addition to carbon dioxide reduction, EV systems powered by renewable energy minimized pollutants such as NO_2, SO_2, and CO that improved public health and quality of air in urban setups (Bicer & Dincer, 2018).

However, the development of the large-scale implementation is still a problem in developing countries such as Pakistan because of the problems with the infrastructure, policy, and the reliability of the energy. Energy strategies based on AI should be integrated to hasten the use of EVs and achieve sustainable transportation. AI optimization further saves energy, decreases reliance on the grid, and increases battery lifespan (Lund, 2015; Mosavi et al., 2019). As central to the study's analytical focus, AI-assisted EVCI provides various environmental advantages that include emission reduction, energy efficiency, and enhanced sustainability results.

1.1. Existing Research Gap and Proposal

Current literature has developed the EV charging literature by considering the charging technologies, smart-grid integration, optimization models, and the overall policy pathways; however, there are three significant gaps (International Energy Agency, 2025; Unterluggauer et al., 2022). First, the literature is mostly focused on mature or fast-growing EV markets, whereas relatively little research has been done on the relationship between charging-infrastructure barriers and affordability, grid unreliability, regulatory uncertainty, and market readiness in Pakistan (Masood et al., 2024; Zia et al., 2025). Second, previous research often investigates infrastructure planning, grid effects, or charging optimization in isolation, and the joint impediment of transport demand, power-network constraints, and policy design remains divided (Unterluggauer et al., 2022). Third, although AI-based methods are increasingly discussed in the broader EV literature, there is still limited synthesis linking these tools to Pakistan-specific EVCI barriers and policy implementation needs. This study addresses these gaps by integrating a systematic review of global and Pakistan-relevant literature with expert insights to identify the major challenges of EVCI development in Pakistan and to map AI-enabled solutions that are aligned with the country's policy and infrastructure context.

This study focuses on EVCI development and investigates it through a Systematic Literature Review (SLR) and a focus group study. Beyond conventional policy analysis, this study introduces AI-enabled solutions to address EV infrastructure, grid, and policy-driven challenges. Machine learning (ML), Reinforcement Learning (RL), digital twins, and lightweight ensemble models are proposed to enhance charging station placement, forecast grid load, optimize tariffs, and simulate policy outcomes. Recent advances in computationally efficient ML architectures demonstrate that lightweight ensemble models can achieve performance comparable to deep neural networks (DNN) while reducing complexity and training overhead (Niazi et al., 2025). Similarly, AI-driven surrogate modeling and hybrid optimization frameworks have shown strong potential for accelerating complex system planning while maintaining predictive fidelity (Shereen et al., 2025). This work will offer a future-proof and scalable route to assist with EV adoption in Pakistan and enhance national climate objectives by integrating policy analysis with AI-based data-driven optimization.

Based on this, the research aims at achieving three goals: (1) to systematically describe the key technical, financial, regulatory and social challenges that impact the development of EVCI in Pakistan; (2) to compare these issues with the findings of the global EV charging literature to identify which of them are context-specific and which are structurally similar across markets; and (3) to suggest AI-enabled solutions that may be used to support the infrastructure planning, grid management, and policy effectiveness in alignment with Pakistan's EV transition goals.

2. Systematic Literature Review (SLR) and Focus Group Study

This section carries out the main research approaches adopted in this study to identify and explain technical, financial, regulatory and social challenges of EVCI in Pakistan for the adoption of EVs by 2030 as per NEVP 2019.

2.1. Systematic Literature Review (SLR)

The SLR approach is valuable for its structured and unbiased process of collecting, analyzing, and synthesizing existing research. As per Kore and Koul (2022), SLR is chosen over other methods as it is a systematic, scientific and reproducible approach and is accepted worldwide. To ensure clarity and thoroughness in this study, a four-step PDCP (Plan/Do/Check (Analyze)/Propose) framework was integrated with the SLR methodology, as influenced by (Kore & Koul, 2022). Table 1 displays the PDCP approach used in our study.

2.1.1. SLR Methodology Adopted

To address the methodological rigor and transparency, this research follows an SLR approach using the principles of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Page et al., 2021). The literature search was done in four leading academic databases, including Google Scholar, IEEE Xplore, ScienceDirect, and Mendeley, covering published articles from 2008 and 2024, a period capturing the studies from initial development to recent progress in EVCI. Using Boolean operators to refine search results, keyword combinations were used such as "Electric Vehicles," "Charging Infrastructure," "Electric Vehicle Charging Stations," "Artificial Intelligence," "Machine Learning," "Smart Charging," and "Electric Vehicle Policies".

Table 1
Four stages of the adopted SLR

Stages	Scope	Details	Article Sections
Plan	Problem identification and setting of the research questions	Previous studies identified the development of EVCI as the deciding factor for faster adoption of EVs. Also, knowing the status of GOP to position EVCI in Pakistan became an essential factor. Hence the research questions are set to fulfil the aims of this study.	Section 2
Do	Select articles using keywords and database	The inclusion and exclusion criteria used select keywords, language, time period, book chapters, duplications and relevance in EVCI.	
Check (Analysis)	Analyse and categorize the literature	The insights were captured through a comparative analysis of global vs local (Pakistan) perspective and synthesis of reviewed literature. In addition, the focus group study was conducted to get additional data and expert opinions on the research gap.	
Propose (Reporting)	Discuss and report findings with clear way forward	Technical, financial, regulatory, and social challenges were discussed, with clear actions detailed by GoP in terms of incentives/policies and backed by AI-enabled solutions for each challenge and incentive/policy.	Section 3

The screening was done in four phases. To begin with, there were 500 records that were searched using the database. Second, 120 overlapping records were eliminated, which led to the screening of 400 unique studies in terms of titles and abstracts. Third, 250 studies were eliminated that were irrelevant to EVCI, leaving 150 articles to review in full text. Fourth, 95 articles were further narrowed down using predefined inclusion criteria (e.g. methodological unsoundness, irrelevance to EVCI or inapplicability to Pakistan or similar settings), and a final sample of 55 studies was included in the SLR.

The inclusion criteria were restricted to peer-reviewed articles and conference papers on the topic of EVCI planning, grid integration, and policy frameworks, as well as AI-based optimization. Duplicates, non-English and non-peer-reviewed publications and studies that were not empirical or methodologically valuable were excluded. The process of selection is outlined with the help of a PRISMA-like flow diagram (Figure 1) that guarantees clarity and reproducibility.

2.2. Focus Group Study

To enhance the results of the SLR and include experienced-based insights, a focus group researched out with a total of nine experts (n = 9) sampled using purposive sampling criteria on the basis of their experience in the field of EVs, power systems, sustainability, and AI. The panel of experts comprised one Assistant Professor in the College of Electrical and Mechanical Engineering (E&ME), NUST, knowledgeable in AI in engineering systems; one Assistant Professor in Florida State University knowledgeable in Explainable AI and cybersecurity; three PhD researchers in Florida A&M University researching on AI applications in power systems, grid reliability, and ML; three solution experts and business development professionals from Huawei Digital Power, Huawei Technologies Co. Ltd. with experience in EV infrastructure, smart energy systems, and data center power solutions; and one Senior Manager in Climate Change and Sustainability Services (CCaSS) at EY with experience spanning energy policy, sustainability strategy, and carbon accounting. This pool of diverse experts provided a balance of academic, research, industry, and policy perspectives, particularly aimed at Pakistan's ongoing EV ecosystem.

The selection of experts was based on three criteria: (i) research or professional experience in EVs or energy systems, sustainability, or AI-enabled applications; (ii) knowledge/experience of infrastructure planning, grid integration, or policy implementation; and (iii) the capacity to give context-specific analysis that is applicable to emerging economies, particularly Pakistan.

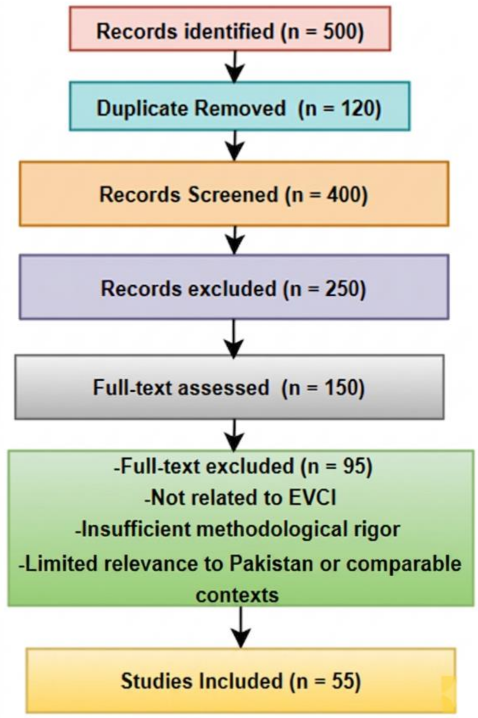


Figure 1: **PRISMA-styled Selection Process for SLR**

The process of engagement was divided into four steps. Step 1 involved the briefing of the chosen experts on the purpose of the study, including the discovery of EVCI challenges with the suggested AI-based solutions, and the provision of an overview of the preliminary SLR results to validate the study. Then in step 2, a semi-structured questionnaire was developed on Google Forms that incorporated both domain-specific and AI-oriented open-ended questions as follows: (Q1) How is Pakistan moving towards the 2030 goal of 30% EV adoption? (Q2) How do you believe the positioning and coverage of Electric Vehicle Charging Stations (EVCS) are now? (Q3) What are the key technical, financial, social and policy problems that need to be resolved to accelerate EVCS deployment? (Q4) What are the ways that AI-based systems like ML, RL or predictive analytics can be used to plan and operate EVCI in Pakistan? (Q5) What do you see as issues or constraints in the application of AI-based solutions in the EV ecosystem in Pakistan, specifically, in the form of data availability, infrastructure preparedness, and policy facilitation? Step 3 involved the collection of responses in a digital format and using Microsoft Excel to compile them in a structured dataset to further analyze them. Step 4 involved the analysis of the responses collected with the use of qualitative thematic analysis method, where the responses were coded into major concepts, organized into categories and synthesized into wider themes that represented repeated challenges in EVCI and problem-solving perspectives. These themes were triangulated with the results from SLR so that consistency, validity, and holistic understanding of EVCI issues and AI-solvable solution paths could be explored in Pakistan.

This dual approach to methodology enhances the credibility of the research as it incorporates theoretical facts with practitioner-informed knowledge, especially when it comes to emergent and data-driven EV infrastructure systems.

Table 2
EV Literature (SLR): Global Context

Author	Target Country	Major Objective	Methodology Adopted	Key Findings
Weinert et al. (2008)	China	To analyze the institutional, market, and technological forces influencing EV adoption in China	Force Field Analysis combined with policy and market assessment.	Identified enabling factors such as battery technology improvements and infrastructure expansion, while highlighting barriers including policy uncertainty, fuel pricing structures, and consumer perceptions favoring conventional gasoline vehicles
Foley et al. (2010)	Global/ International	To review the state-of-the-art of EVCI and standards	Technical literature review and comparative assessment of international charging practices	Synthesized global best practices in charging standards, grid integration, and infrastructure deployment strategies, emphasizing the importance of harmonized standards and coordinated rollout planning
Mak et al. (2013)	Global/ International	To develop optimization models for planning EV battery swapping infrastructure	Mathematical programming and facility location optimization model	Proposed analytical models to determine optimal battery swapping station locations under demand uncertainty, balancing service coverage, cost efficiency, and system reliability
Yilmaz and Krein (2012)	Global/ International	To classify and review integrated charging methods for plug-in electric and hybrid vehicles	Technical literature review and system-level analysis	Provided classification of charging levels, power electronics architectures, and infrastructure integration approaches, including implications for state-of-charge management and grid interaction
Rahman et al. (2014)	Global/ International	To review optimization and planning approaches for EV/PHEV charging infrastructure deployment	Review of mathematical and optimization-based planning models	Evaluated infrastructure planning models addressing siting, cost minimization, load balancing, and system-level efficiency improvements
Neaimeh et al. (2017)	United Kingdom	To analyze real-world usage patterns of fast chargers and assess their role in EV adoption	Empirical data analysis using real-world charging datasets and regression modeling	Demonstrated that access to fast charging significantly enhances EV usability and reduces range anxiety, reinforcing its importance in large-scale adoption strategies
Shaukat et al. (2018)	Global/ International	To review EV integration within smart grid environments	Comprehensive survey of V2G technologies and grid integration frameworks	Highlighted the potential of V2G systems to improve grid stability, renewable integration, and demand-side management through coordinated charging strategies
Statharas et al. (2019)	Europe	To model EV penetration scenarios in Europe under varying policy conditions	Sensitivity analysis using techno-economic and policy-driven modeling frameworks	Identified policy stability, infrastructure investment, and battery cost reductions as critical determinants for accelerating EV penetration by 2030
Ahmad et al. (2020)	Global/ International	To evaluate the technical feasibility and operational challenges of battery swapping stations	Technical analysis and system-level assessment of battery swapping station integration within smart grids	Assessed opportunities and limitations of battery swapping models, emphasizing grid impact considerations, operational coordination, and standardization requirements

The focus group study identified four main barriers to successful EVCI adoption: (i) the challenge of estimating construction costs of EVCS and financially viable user-end tariffs; (ii) the challenge of identifying the optimal site selection because of limited demand and mobility data; (iii) the challenge of unclear regulatory frameworks to determine standards, pricing, and participation of the private sector; and (iv) the challenge of low public awareness and understanding of stakeholders on government incentives and subsidies pertaining to EV adoption. The experts additionally stressed the importance of AI-based tools in demand forecasting, dynamic pricing, infrastructure planning, and grid integration, while also indicating limitations in the availability of data, technical capability, and deployment readiness in Pakistan.

Global Context on EVCI: EVCI has been progressively implemented on a large scale in the developed economies (especially in China and the European Union) over the last decade, but large regional differences remain. Over 1.3 million public charging points were installed globally in 2024 alone – with most of the growth occurring in China – and the increase in global public chargers has grown to over 5 million since 2022; yet even in developed markets, there is an unevenness in chargers per EV numbers and network penetration among countries and regions. Although countries like Norway, the Netherlands, and China have high EV adoption rates, most of the developed countries are still lagging behind the growth in demand because of the slow pace in charging infrastructure installation and integration of the grid together with regulatory challenges (International Energy Agency, 2025). The charging infrastructure siting and capacity planning is a complicated issue, especially with alternative architecture like battery swapping, where joint facility location and operation modeling is required (Mak et al., 2013). Other studies focus on strong policies on battery swapping systems, advances in battery chemistry, and reduced battery sizes in faster EV adoption. Also, the impediments to EV adoption vary regionally, influenced by unique policy settings, infrastructure development, and market preparedness. Table 2 below covers the global EV perspective considered under the SLR.

Pakistan's Context on EVCI: The context in Pakistan on EVs is still early with limited charging infrastructure, disjointed data, and changing policy models, in contrast to developed markets like China and Europe that have the backing of a well aligned, stable policy and grid preparedness. Whereas global studies focus on optimization of charging density, accessibility of fast charger, and grid-coordinated planning, the problem gaps facing Pakistan are more fundamental, such as weak infrastructure, weak regulations and weak technical capacity. Such problems affect investor trust and uptake, which is why context-based approaches, rather than direct imitation of international examples, are necessary (Zia et al., 2025; Zulfiqar et al., 2024). Thus, the global practices have to be tailored to the local realities of Pakistan, including the reliability of power system, economic limitations, and the capacity to execute policies.

3. Discussions and Findings

In this study, ten significant obstacles to the development of EVCI in Pakistan are drafted as a product of SLR and the responses of experts to the focus group study. Considering every challenge, an AI-enabled solution and its short working mechanism are suggested. The solutions based on AI are also combined with GoP policies and existing market insights, which demonstrate how data-intelligent processes can assist in policy implementation and speed up the move towards the 30% EV adoption goal by 2030.

3.1. Technical, Financial, Regulatory and Social Challenges of Developing EVCI in Pakistan

To ensure coherence and strengthen analytical approach, the EVCI challenges are divided into four categories: technical (e.g., grid instability, charging speed, infrastructure constraints), financial (e.g., high costs, investment risks), regulatory (e.g., policy inconsistency, absence of standards), and social (e.g., range anxiety, low consumer-side awareness). While every challenge is discussed in detail separately, this grouping shows their interdependence and offers a systematic insight into the influence of multiple obstacles in the development of EVCI in Pakistan.

Challenge 1 - Lack of charging stations (Technical/Regulatory): Pakistan has minimal charging stations, and expensive installations are still a challenge, but with government incentives such as reduced EV electricity tariff, automakers, power companies and businesses are looking to invest. Firstly, the NEVP 2019 drafted the installation of at least one DC fast charger in every 3x3 km urban grid and the installation of DC fast chargers along the motorways and highways with 15-30 km intervals to guarantee network coverage (MoCC, 2021). Based on this premise, the New Energy Vehicle Policy 2025-30 continues to expand the national ambition, aiming to have 3,000 public charging stations across the country by 2030 and install 40 fast chargers along motorways to enhance intercity connectivity and large-scale EV adoption (MoI&P, 2025). Although the global planning models optimize the infrastructure placement in the presence of uncertainties in the demand (Mak et al., 2013), and coordinated rollout strategies enhance coverage (Foley et al., 2010), the charging network in Pakistan continues to be limited, revealing a disparity between optimization-based planning and realistic implementation.

AI-enabled Solution: Through demand-aware sitting with ML and Geographic Information System (GIS), the placement of charging stations can be optimized to maximize their utilization, spatial coverage, and grid feasibility. Latest GIS-based optimization models that integrate clustering algorithms with multi-objective algorithms have shown better rates of charger utilization and lower infrastructure underutilization in urban areas. Moreover, facility-location models that are used on planning EV infrastructure indicate that the data-driven sitting can considerably improve spatial coverage and reduce the cost of deployment in situations of demand uncertainty (Li, 2025; Mak et al., 2013; Zhang et al., 2025).

Stepwise Working: (a) Train demand models using traffic data, land-use patterns, EV ownership density, and Point of Interests (POIs); (b) cluster candidate sites via GIS using K-means and multi-objective optimization through Nondominated Sorting Genetic Algorithm III (NSGA-III) **–** a multi-objective optimization **–** combined with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) **–** a decision-making method **–** to balance cost, accessibility, and grid constraints (Li, 2025; Zhang et al., 2025) (c) after deployment, apply RL-based simulators to manage charger utilization and dynamic load balancing under operational constraints (Mosalli et al., 2025).

The stepwise working is further displayed in figure 2. This figure contributes to the results of Challenge 1 by transforming the suggested AI-powered siting solution into a sequence of analytical operations. It is relevant to its methodology because it demonstrates how spatial information, clustering techniques, and multi-objective optimization can be used together to reflect the infrastructure planning needs into a set of implementable charger-location decisions. This is initiated using GIS data that includes population centers, land use, power grid accessibility, and the traffic density. Clustering algorithms like NSGA-III or K-means are used to analyze this data to recognize high-demand zones. Potential configurations are then evaluated using multi-objective optimization algorithm considering rates of charger utilization, cost limits, and grid feasibility to identify the most efficient and balanced station layout (Li, 2025; Zhang et al., 2025). This type of data-driven siting reduces unused infrastructure and achieves even coverage of network to enable high-volume EV adoption and effective power distribution.

Challenge 2 - High upfront costs (Financial): Purchase cost of the vehicle is the major problem facing EV industry. In Europe, EVs are encouraged by the policy stability models and cost-saving systems (Statharas et al., 2019), but Pakistan remains under the affordability pressure caused by lack of incentives and market maturity. EVs tend to be costlier to manufacture over Internal Combustion Engines (ICE) vehicles, mostly because of battery technology and the use of costly raw materials to create high-capacity batteries. Also, there is still a greater ICE vehicle supply and demand globally, even when discounting

EV batteries. Though EVs have considerably lower operating expenditures (OPEX) in comparison with gasoline counterparts, their initial cost of purchase is relatively high. The number of EV models that cost less than USD 30,000 is growing, especially in China, but affordability remains a limiting factor in most markets (International Energy Agency, 2025). The challenge, however, gets better as more EVs gain market penetration, government policies get better, and battery technology advances, making the initial costs cheaper.

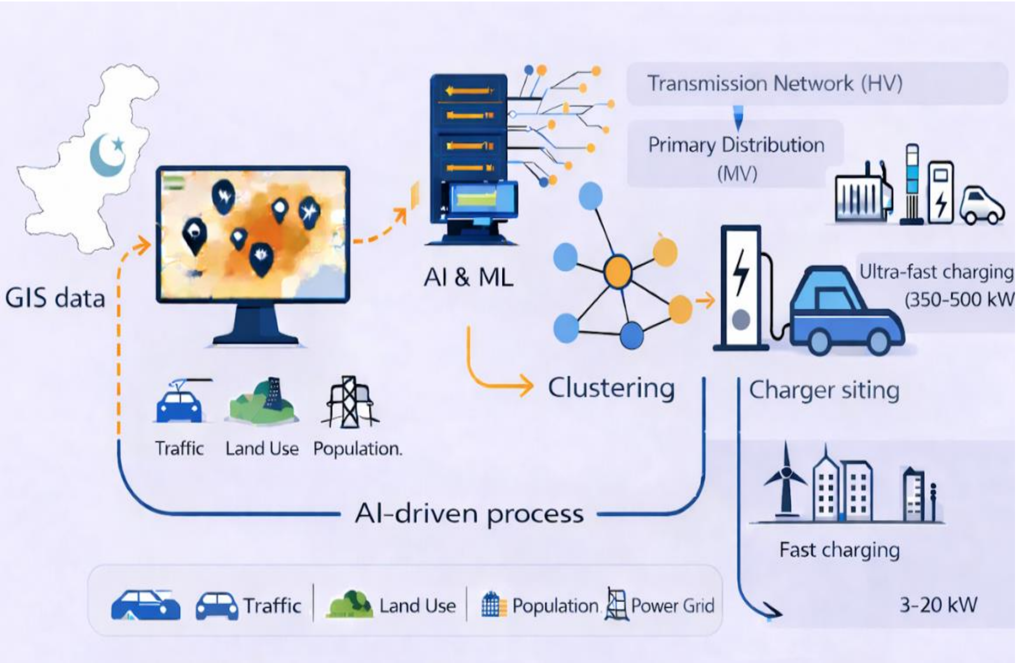


Figure 2: **Proposed Framework for AI-driven Siting Process**

AI-enabled Solution: With the help of ML forecasting and policy optimization, subsidies/tariffs can be focused on the area where each rupee (PKR) brings the latest EVs. Secondly, dynamic prices will assist in reducing charging station OPEX. Recent research shows evidence that ML-based demand forecasting and dynamic pricing models can enhance the financial sustainability of EV charging networks. Forecasting models based on Long Short-Term Memory (LSTM) – a type of recurrent neural network – and gradient boosting demonstrated elevated prediction accuracy for charging demand and allows more optimized subsidy targeting and planning infrastructure. Moreover, RL-based pricing has been demonstrated to minimize peak loads and enhance stability in operator revenue in simulated EV charging markets (Cui et al., 2023; Matkovic et al., 2024; Siddiqui et al., 2025).

Stepwise Working: (a) ML Gradient Boosted Machine or Gradient Boosting Model (GBMs)/ LSTM predicts EV charging demand and utilization patterns; (b) a policy optimizer gives precedence to subsidies and tariff incentives aimed at high-demand consumer groups based on estimated adoption trends; (c) Deep Reinforcement Learning (DRL)-based dynamic pricing optimizes peaks and enhances operator revenue predictability; (d) big data dashboards monitor spend and outcomes to adjust incentives (Alaraj et al., 2025; Cui et al., 2023; Matkovic et al., 2024; Wu et al., 2025).

Challenge 3 - Charging infrastructure resilience (Technical): EVCS are vulnerable to the unavailability of electricity on the grid, mainly experiencing brownouts (partial grid outage) and blackouts (complete grid outage) that are symptoms of structural vulnerability in transmission, distribution capacity, and load management. Experts also underscore the uninterrupted power supply (UPS) installed on charging stations as a need, further advising assessment and capacity planning in terms of sustainable power distribution networks that consider the current transformation capacity, load flow, and integration of renewable energy. Although solar-integrated EVCS can make the grid resilient and meet the renewable energy targets of NEVP 2019 (MoCC, 2021), the aging transmission network and distribution limitations in Pakistan suggest that overall grid modernization is required to implement large-scale EV adoption. EV charging globally is becoming more and more connected with the smart grid and V2G systems to improve grid stability (Lund, 2015; Shaukat et al., 2018), but in Pakistan the power system is not very reliable and impedes such integration.

EVCS integration, technically, involves several voltage levels of the national grid - the generation of electricity at medium voltage is stepped up to high-voltage transmission (e.g. 500/220 kV), and then stepped down at substations (132 kV to 11 kV) before converting AC supply to DC at fast chargers to fit battery requirements. EVCS can be connected at HV, MV, or LV based on station capacity and demand profile, as shown conceptually in the UNDP framework (Raza, 2021). Figure 3 gives the electrical-system context of Challenge 3, indicating the interaction of EVCI with transmission, sub-transmission, distribution, and end-use conversion stages. Its applicability to the challenge is that it explains why the resiliency of charging stations in Pakistan should not just be evaluated at the charger level, but also in connection with feeder loading, substation capacity, and AC/DC conversion limitations.

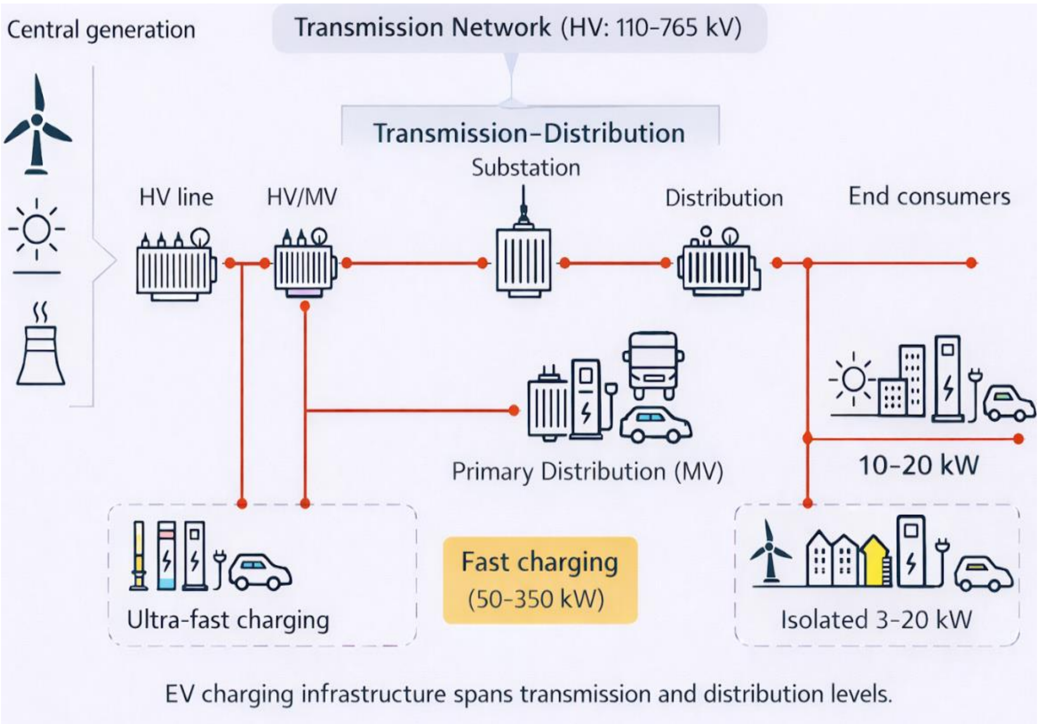


Figure 3: **Conceptual Schematic of EVCI Across Transmission and Distribution Levels, Based on (Raza, 2021).**

AI-enabled Solution: With short-term load prediction and DRL scheduling, it will be possible to maintain station demand within feeder/transformer constraints and achieve maximum throughput. Empirical and simulation-based studies have shown that AI-based load forecasting and control methods can help to substantially improve grid stability in EV-based systems. Deep learning-based short-term forecasting models like LSTM and Temporal Convolutional Networks (TCNs) have demonstrated a high level of accuracy in charging demand forecasting, allowing proactive load control. In parallel, DRL-based energy management systems have shown the ability to optimize charging schedules, reduce peak demand, and improve integration of renewable energy sources within distribution networks (Colak & Fescioglu-Unver, 2024; Han et al., 2024; Paudel & Das, 2023).

Stepwise Working: (a) LSTM/ TCNs predict 15-60 min EVCS load; (b) a Deep Q-Network (DQN)/DRL controller coordinates charge rates, onsite Photovoltaic (PV)/ Battery Energy Storage System (BESS), and Volt/Var actions, shifting flexible sessions to off-peak and shaving peaks in real time (Colak & Fescioglu-Unver, 2024; Han et al., 2024; Mosalli et al., 2025).

Challenge 4 - Range anxiety (Social): Range anxiety refers to the fear element experiencing EV owners to run of battery power before a destination is reached. Empirical research in the United Kingdom indicates that the availability of fast chargers can considerably lower range anxiety (Neaimeh et al., 2017). In Pakistan, however, range anxiety exists primarily due to very limited and focused charging infrastructure. In cold weather, especially during winters, the effective range of driving can decrease significantly (by up to 20-40%) because of battery energy losses and HVAC loads. The intentions of the NEVP to install DC fast chargers on motorways will address this issue, providing inter-city charging opportunities. The majority of the EVs sold can travel 300-500 km with a single charge. On long intercity routes such as the approx. 380 km route between Islamabad and Lahore on the M2 motorway, there must be at least one charging station installed.

AI-enabled Solution: With eco-routing and individualized range prediction we will be able to reduce energy consumption and deliver precise and driver-specific remaining range estimates. Empirical and simulation research confirm that AI-based eco-routing and range prediction models have a considerable positive effect on the confidence of users and the efficiency of operations. ML-based models of range estimation have shown better predictions of battery consumption in different driving conditions, and data-driven routing algorithms that include traffic, terrain, and weather information have shown significant energy savings. Empirical studies also attest that the perceived range anxiety is minimized and the EV usability is increased by ensuring access to optimized charging and routing information (Chen et al., 2022; Neaimeh et al., 2017; Woo et al., 2024).

Stepwise Working: (a) Eco-routing reduces energy consumption (rather than distance) using grade, speed, traffic, and temperature; (b) a range prediction model (e.g., XGBoost/LSTM) modulates for driver style and HVAC load to give accurate remaining range evaluations (Caferler et al., 2025; Chen et al., 2022; Woo et al., 2024).

Challenge 5 - Electricity shortfall, battery manufacturing capabilities and scarcity of battery raw material affecting standardization (Technical/Financial/Regulatory):
Pakistan is currently experiencing electricity deficit, which is one of the reasons why people are not adopting EVs. Electricity is expensive in Pakistan, and a way to make it cheaper for EV users is to install solar PV charging stations, where people would be charged economically due to minimal OPEX of renewable energies. EV charging requirements mainly rely on battery specifications. The battery is a vital and most expensive part of an EV, with a 40-50% cost component weightage. The capacity and voltage of batteries vary with different EV segments. The most common and economical batteries in use is Lithium-ion batteries. Improving Lithium-ion battery performance with reduced size and lower costs are live areas for R&D. The three leading countries for exporting lithium are Australia, Chile and China. If mines are not available domestically, reserving the mining capacity from the three mentioned countries, with ample quantities, needs to be explored to bring down overall battery costs. Additionally, battery recycling is a key component of the global circular economy due to environmental risks of improper disposal, with advanced systems focusing on lifecycle optimization and standardization (Ahmad et al., 2020; Sun et al., 2025; Wang et al., 2024) Pakistan, contrary, remains dependent on imported raw materials with limited recycling capability. Since Lithium-ion batteries are the most critical in the entire value chain, Pakistan would have to make strategic partnership to secure supply of key raw materials in battery manufacturing like Lithium, Cobalt and Nickel to indigenize and meet the increasing demand by 2030. A direction Pakistan can take is a strategic partnership with China that dominates the battery production industry currently.

AI-enabled Solution: With battery State-of-Health (SoH) ML and AI-assisted recycling, it is possible to increase pack life and recovery outputs of Lithium, Cobalt and Nickel. Recent empirical research shows that ML-based battery SoH and Remaining Useful Life (RUL) – battery life prediction – models could effectively forecast degradation trends, allowing to optimally plan charging and increase battery life. Moreover, AI-assisted computer vision and automation-based recycling systems have demonstrated a higher efficiency of material recovery and cost-effectiveness than traditional systems. In addition to that, techno-economic evaluations indicate the ability of automated disassembly to boost the recovery of key materials, including lithium, cobalt, and nickel that supports the goals of circular economy (Antony Jose et al., 2024; Cao et al., 2025; Choux et al., 2024).

Stepwise Working: (a) SoH and RUL models predict degradation using voltage/current/temperature signatures to implement adaptive charging policies (Sylvestrin et al., 2025) (b) computer vision and ML systems control robotic disassembly and material sorting to recover materials with higher purity (Antony Jose et al., 2024).

Figure 4 shows how the battery SoH and RUL prediction can be used with AI-assisted recycling to enhance the lifecycle management and material recovery of lithium-ion batteries. ML-based prediction of battery degradation trends is based on real-time sensor data, which includes voltage, current, and temperature measurements to support adaptive charging approaches to increase pack life. At the same time, computer vision algorithms detect, categorize and sort used cells in the disposal process, directing robotic dismantling to effectively retrieve materials with Li-/Co-/Ni-bearing compounds. This unified system lowers wastage, improves recovered outputs, and contributes to sustainable battery supply chains. Thus, this figure emphasizes a single lifecycle perspective. Its methodological role is to show that AI in this study is adopted not only to charging optimization, but also to battery sustainability, material recovery, and extended supply-chain stability.

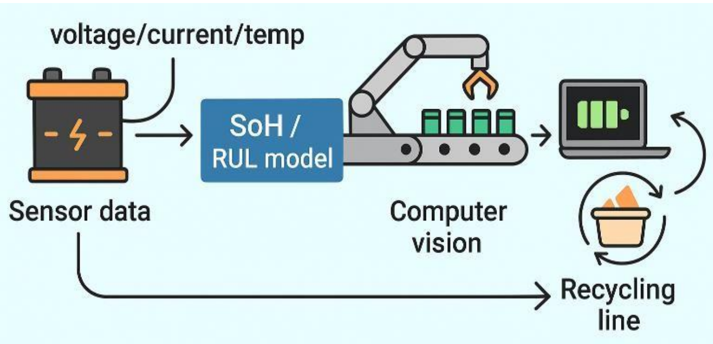


Figure 4: **Conceptual Model of AI-based Battery Health Prediction and Recycling**

Challenge 6 – Barriers to production scale-up (Technical/Financial/Regulatory): In Pakistan, scaling up local manufacturing for EVCI remains challenging due to insufficient industrial infrastructure required for large-scale deployment. In contrast, China's EV ecosystem demonstrates strong industrial capacity supported by coordinated manufacturing growth and policy alignment (Weinert et al., 2008). In Pakistan, advanced manufacturing technologies, supply chain efficiencies, availability of specialized materials and equipment, and skilled technical staff are all limited. Moreover, the local R&D presence in EV parts is still small, and the financial aspect of the production of batteries, power electronics, and EV motors is capital-intensive, establishing additional financial obstacles to domestic companies. Therefore, Pakistan has insufficient businesses that can develop and scale EVCS indigenously currently.

AI-enabled Solution: With the help of virtual factory models and predictive maintenance based on digital twins, manufacturers will be able to detect bottlenecks (i.e., process constraints that limit production throughput), decrease downtime and boost production performance. Digital twin technology has been applied to industries where it has shown that manufacturing efficiency and system reliability have improved (Yang et al., 2024). Simulations in virtual factories allow the discovery of process bottlenecks and optimization of the production processes before the physical implementation, lowering the cost of trial-and-error. Also, AI-based anomaly detection as a predictive maintenance model has been demonstrated to minimize downtime and enhance the usage of equipment in sophisticated manufacturing systems (Yildiz et al., 2021).

Stepwise Working: (a) A digital twin of a plant replicates equipment and process flows digitally; (b) predictive maintenance is performed with anomaly detection using vibration and thermal signals; (c) virtual factory simulations are used to test the performance of the production line and capacity limits prior to actual implementation (Yildiz et al., 2021).

Challenge 7 - Policy inconsistency and regulatory changes (Regulatory): According to the New Energy Vehicles Policy 2025-30, Pakistan's EV charging ecosystem primarily operates through two infrastructure models: conventional battery charging stations (AC/DC) and battery swapping stations, particularly for 2/3-Wheeler (2W/3W). However, the revenue model for businesses remains undefined, leaving uncertainty around pricing, grid connection, utilization rates, and operational costs – discouraging private sector investment. By contrast, China's coordinated public-private strategy has enabled ultra-fast charger expansion across more than 400 cities, with automakers planning to deploy 20,000 ultra-fast chargers nationwide; this scale-up has been supported by strong industrial collaboration and policy backing (International Energy Agency, 2025). Drawing on China's example, Pakistan's policymakers and automakers need to clarify business models, tariff regulations, and public-private frameworks to enable widespread and sustainable EVCI rollout.

AI-enabled Solution: With regulatory sandbox and DRL-based dynamic pricing (as mentioned in challenge 2) we can experiment on the tariffs/subsidies and select the policies that are stable and can be invested in. Recent energy market research indicates that policy simulation algorithms based on AI and dynamic pricing models can be much more effective in regulatory decision-making. The combination of agent-based modeling with RL has been applied to test tariff structures and subsidy mechanisms at different demand conditions, allowing policymakers to strike the right balance between grid stability, consumer uptake, and returns to investors. These strategies have demonstrated high potentials of minimizing uncertainty and enhancing policy performance in the long-term at emerging energy markets (Cui et al., 2023; Matkovic et al., 2024).

Stepwise Working: (a) Agent-based demand and DRL pricing models the results (adoption, peaks, operator margins) under policy bundles; (b) select the bundle that clears grid KPIs and private internal rate of return (IRR) – an investment indicator – limits; (c) the regulatory sandbox tests adaptive tariff structures in pilot areas, using demand-driven DRL pricing simulations to test operator margins, peak smoothening and investment feasibility before wider deployment, allowing real-world assessment to optimize tariff structures and investment incentives (Cui et al., 2023; Matkovic et al., 2024).

Challenge 8 - Location of charging stations (Social/Regulatory): EV users are commonly experiencing issues related to placement of the charging points/stations, which greatly influences their driving experience. Poor infrastructure, or lack of conveniently placed charging stations, even in an urban city, can lead to frustration in finding appropriate locations to charge. Additionally, the charging points may be overcrowded or inaccessible, which can lead to delays and alterations of journey plans for EV owners. Data-driven siting methods based on demand modeling and infrastructure planning have been proposed by global optimization studies (Mak et al., 2013; Rahman et al., 2014), whereas Pakistan's planning is not as structured and data-driven. As NEVP 2019's recommendation, atleast one DC fast charger should be placed in every 3x3 km dimension and along motorways and highways after every 15-30 km.

AI-enabled Solution**:** Mobility-data clustering and multi-objective siting can be used to place chargers in empirically high demand hotspots and take into consideration the grid feasibility and cost limitations. The empirical mobility-data analyses indicate that clustering-based and multi-objective optimization methods enhance the availability and usage of the charging stations. These models can determine high-demand charging areas by using GPS and Origin-Destination (OD) data and optimally place infrastructure based on real travel behavior. The outcomes of simulation show that these strategies help decrease the waiting time, increase service coverage, and improve the efficiency of the entire network (Li, 2025; Zhang et al., 2025).

Stepwise Working: (a) Gather anonymized GPS and OD travel-demand data on vehicles and mobility platforms to establish common points of stop and increased traffic routes. Group this data with algorithms like K-means to identify natural charging demand hot spots. (b) Develop a multi-objective siting optimization model that addresses cost of installation, accessibility to the user, grid capacity limits, and spatial equity. Optimize this with GIS-based optimization methods like NSGA-III with TOPSIS or data-fusion-based models and rank candidate locations to identify the best charger (Li, 2025; Zhang et al., 2025). Solve this using GIS-integrated optimization techniques such as NSGA-III, combined with TOPSIS, or data-fusion-based frameworks to rank candidate sites and select optimal charger (Li, 2025; Zhang et al., 2025).

Challenge 9 - Skilled workforce for EV maintenance (Technical/Social): Most car owners find that having their vehicle serviced by a dealer can be significantly more expensive than using a qualified independent maintenance and repair shop. In China and other developed EV markets, workforce development has progressed alongside EV growth (Weinert et al., 2008). Pakistan, however, faces a shortage of trained technical personnel for EV systems. With the EV industry still comparatively small, there are relatively few trained EV repair technicians and even fewer qualified independent shops. Working on an EVs beyond tires, brakes, light bulbs and audio components can be dangerous for an untrained technician. Luckily, EVs needs less maintenance than ICE vehicles. However, when a part needs replacement, like the costly battery pack ranging from USD 5,000 to USD 20,000 as dependent on battery size, make, model and warranty coverage (AAA, 2024) – the EV market provides very few cost-saving options.

AI-enabled Solution: An EV maintenance system based on digital twin, can model the behavior of a high-voltage system and Battery Management System (BMS) under a virtual environment to perform predictive diagnostics and allow safe familiarization of technicians with the physical system before performing any physical maintenance (Verma et al., 2024). The recent use of digital twin technology in the training and maintenance setting has shown better accuracy of diagnostics and operational safety. Simulation platforms, powered by AI, enable the technicians to work with virtual high voltage systems, minimizing risk in the field. Research demonstrates that these systems contribute to skill development, decrease human error, and provide better efficiency of maintenance in complex electrical systems (Verma et al., 2024).

Stepwise Working: A real-time digital twin virtually mirrors battery and powertrain parameters (voltage, current, temperature, SoC) to simulate lockout/tag-out operations and fault conditions, while AI-based anomaly detection detects dangerous procedures and refines diagnostic accuracy before heading to the field job (Verma et al., 2024).

Challenge 10 - Slow charging speeds of EV chargers (Technical/Regulatory): EVs charge much slower than ICE vehicles because of battery and charging potential limitations as provided by the Electric Vehicle Supply Equipment (EVSE) i.e. connectors, cables and control systems that constitute a portable charger or charging station to charge an EV. Globally, advancements in charging standards and power electronics have improved charging efficiency (Yilmaz & Krein, 2012), whereas Pakistan's limited deployment of high-power chargers restricts charging speed. There are three primary 'Levels' of EV charging – Level 1, Level 2, and Level 3 – describing power output (kW) and electrical characteristics of EVSE (Raza, 2021). Furthermore, there are four 'Modes' of EV charging – Mode 1 (AC charging), Mode 2 (AC charging), Mode 3 (AC charging), and Mode 4 (DC charging) – which are methods to deliver power to EVs as set by international standards such as the IEC.

Level 1: Used in residential charging for 2W/3W and cars and works on a single phase 220V AC wall socket, requiring no additional circuit, aside from Mode 1 and Mode 2 to connect EVs to the socket. Typical EV batteries take overnight to charge, drawing output up to 3.3 kW (Raza, 2021).

Level 2: Used in residential, work, and commercial places for 2W, 3W and cars, requiring 220-240V AC (or three-phase) on Mode 3 and connectors such as IEC Type 1 (SAE J1772) or IEC Type 2 (Mennekes), drawing outputs between 3.3 kW to 22 kW (Raza, 2021). Most public charging stations are Level 2 or a combination of Level 2 and Level 3 and can take up to 2-10 hours to charge depending on charger and vehicle.

Level 3: Used in transport corridors (Motorways) and highways for cars and buses, equipped with a Direct Current Fast Charger (DCFC) on Mode 4 with plugs/connectors such as CCS Combo 1 & 2, CHAdeMO, GB/T DC, and Tesla connector in providing the quickest possible charge i.e. 20%-80% charging in up to 20-60 minutes. Power outputs are typically rated over 50 kW, and range up to 350 kW (Ultra-fast DCFC) or more (Raza, 2021).

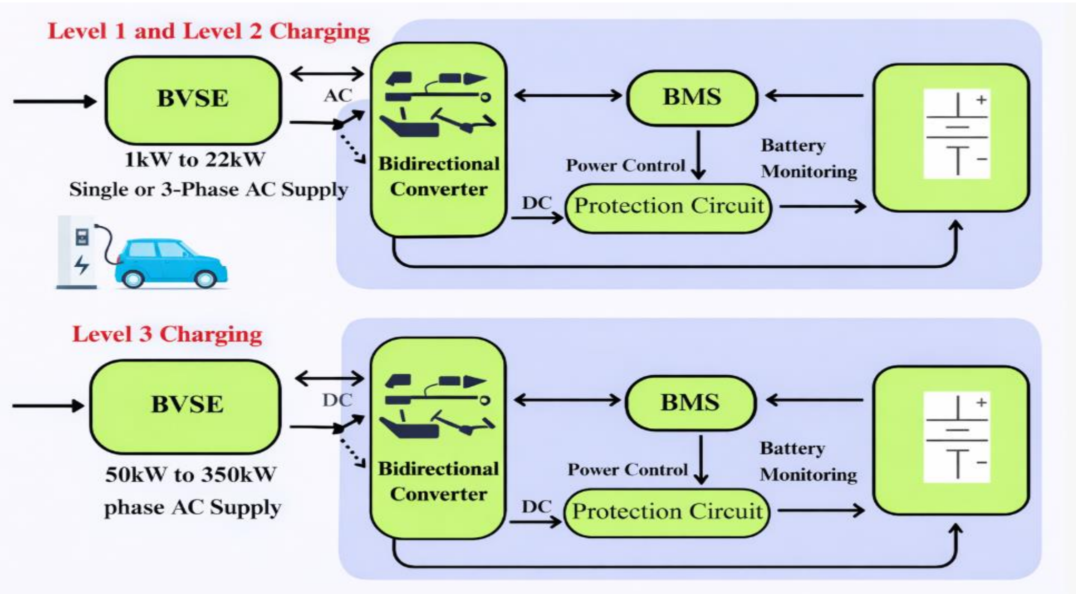
As battery technology improves, EV charging times are expected to reduce substantially. For example, Porsche has achieved DC charging speeds of 18 minutes (under optimal conditions) for 10%-80% for its 2025 Taycan models. While ICE vehicles refuel in seconds, EV charging, even at best, takes 20-60 minutes for a substantial charge. This charging time is often worsened in Pakistan by a critical shortage of public charging spots relative to the number of EVs, leading to potential queues. Thus, there is a vital need to develop efficient fast chargers to cater to such time concerns.

AI-enabled Solution: DRL/Model Predictive Control (MPC) charging control and queue-aware scheduling may be used to enhance the efficiency of charging and maintain battery health, while minimizing waiting time at the station. Smart charging system research shows that AI-based scheduling and energy management can considerably decrease effective charging time and enhance infrastructure usage. It has been demonstrated that RL models can optimize the sequence of charging and power allocation, thereby minimizing waiting periods and maximizing throughput in busy charging stations. Moreover, the integration with energy storage systems also enhances the efficiency of the charging process and grid stability (Colak & Fescioglu-Unver, 2024; Paudel, 2023).

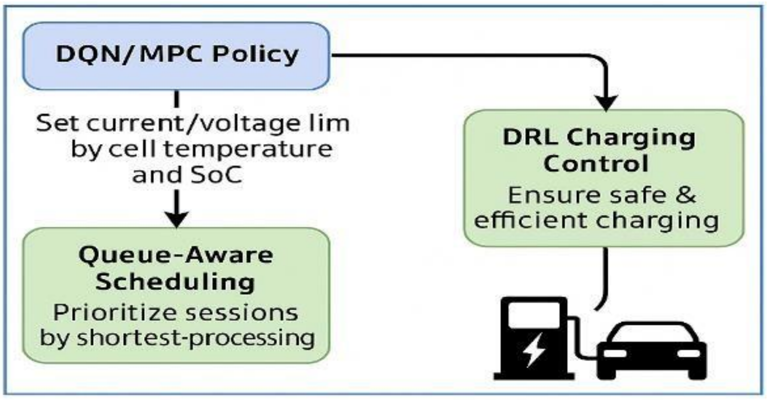
Stepwise Working: (a**)** A DQN/MPC-based control policy calculates optimal current and voltage limits on the basis of real-time battery temperature and SoC, ensuring safe and efficient charging and reducing thermal stress and degradation during fast charging (Abbasi et al., 2024). (b) Simultaneously, a queue-aware scheduling model implements a decision policy based on DQN, which gives priority to charging sessions under operational constraints with a shortest-processing-time-based strategy to reduce the total waiting time and enhance the efficiency of charger utilization (Han et al., 2024).

Figure 5 supports the study by illustrating both the physical charging architecture and the proposed AI-enabled control framework for different levels of charging. Together, the figure links system architecture with intelligent control, showing how the proposed AI framework translates into real-world safe, efficient, and adaptive EV charging operations.

Figure 5 (a) shows the charging mechanism for Level 1 and Level 2 AC chargers and Level 3 DC fast chargers, following the power flow and hierarchical control structure as described in Tayri and Ma (2025), highlighting the interaction between EVSE, bidirectional converters, battery management systems (BMS), and protection circuits that establishes the hardware-level context for charging operations. In Level 1 and Level 2 AC charging, grid AC power is first sent through the Pilot Wire interface that provides communication between the charger and the vehicle. The bidirectional converter, incorporated within On-Board Charger (OBC) processes the AC supply. The converter in charging mode uses a controlled AC-to-DC rectification and sets the voltage and current based on instructions transmitted by the Battery Voltage and State Estimation (BVSE) and BMS. When the converter is in discharging mode (V2G/V2H operation), the converter is used as an inverter, and the battery DC is converted into grid-synchronized AC, allowing the two-way flow of energy. The DC power (converted from AC) is regulated constantly via coordinated control signals between the BVSE and BMS that also observe battery voltage, SoC, temperature, and health parameters. These real time monitoring signals set safe charging limits, optimize charging rate, and protect against battery degradation. In Level 3 DC fast charging, the high AC input from the grid is first transformed into regulated DC by an external bidirectional AC/DC converter inside the charging station. This charging architecture circumvents the vehicle OBC to provide greater power transfer (50-350 kW). Additionally, the station-side bidirectional converter performs power factor correction, DC voltage regulation, and grid synchronization. It also inverts DC-to-AC towards the grid during V2G operations. Even though the OBC is bypassed, battery charging remains actively controlled by the BVSE and BMS with the help of real-time control and monitoring signals (Tayri & Ma, 2025). Conversely, Figure 5 (b) presents the AI-charging control and queue-aware scheduling system. DQN/MPC module controls dynamically the voltage and current based on vehicle SoC and temperature feedback, allowing safe and effective energy transfer. At the same time, the queue-aware scheduler gives prioritized charge sessions with shortest processing-time optimization to reduce total waiting time. This consolidated control architecture balances real-time grid load, reduces congestion during peak demand, and stabilizes the system while enhancing charger utilization (Cui et al., 2023; Han et al., 2024; Matkovic et al., 2024).



(a)



(b)

Figure 5: **(a) Charging technology Architecture for Level 1/2 AC and Level 3 DC Fast Chargers as Adapted from (Tayri & Ma, 2025), (b) AI-based Charging Control and Queue-aware Scheduling System (Cui et al., 2023; Han et al., 2024; Matkovic et al., 2024)**

3.2. Government Incentives and Policy Measures

GoP applied a series of fiscal and operational incentives to curb EVCI problems and encourage EV adoption as shown in table 3, based on the vehicle type. The aim is to reduce the acquisition prices, promote domestic production, and increase consumer confidence. These incentives are intended to lower entry constraints for consumers and manufacturers and promote initial market penetration, particularly in the 2W/3W and the public transport market. 2W/3W were prioritized due to their high market volume and ease of charging infrastructure deployment.

Table 3
Pakistan's EV Incentive Structure by Vehicle Category (MoCC, 2019; EDB, 2020; MoI&P, 2025)

Vehicle Category	GST Rate	Customs Duty	Additional Benefits	Policy Duration
2W, 3W	1% at sales stage; 0% at import	1% on specific parts	Registration and annual token tax exempted; 50% toll reduction	5 years (EV Policy period)
Heavy Commercial Vehicles (HCV)	1% at sales stage; 0% at import	1% on Completely Built Up (CBU) imports; 1% on Completely Knocked Down (CKD) to local manufacturers	Registration, renewal, permit fees waived; 50% toll reduction	Policy period

3.2.1. Manufacturing Incentives

The GoP is also concerned with localizing the EV supply chain with facilitative import and tax regimes. Table 4 summarizes these incentives. The emphasis of GoP on greenfield plants exclusively for EVs highlights the fact that GoP is focusing more on constructing new industrial capacity, rather than swapping/expanding on existing ones. Additionally, establishing the battery recycling system is an essential step in reducing the negative impact on the environment and advancing the concept of circular economy.

Table 4
Manufacturing and Component Incentives (EDB, 2020; MoI&P, 2025)

Component Type	Sales Tax	Customs Duty	Other Incentives	Duration
EV Components (motors, etc.)	0% sales tax	1% on motors, batteries, electronics	5-year income tax exemption for greenfield facilities	5 years from manufacturing start
Recycling Infrastructure	Not specified	1% on components and parts	Must be approved by Engineering Development Board	Policy period
Manufacturing (machinery, equipment, etc.)	Exempted	Exempted for OEMs and vendors	Supports EV-related part production	5 years from manufacturing start
Conversion Kits	Not Specified	1% on component and parts	Must be approved by Engineering Development Board	Policy Period

3.2.2. Infrastructure Planning and Responsibilities

Infrastructure readiness is a critical pillar of the NEVP 2019. NEVP 2019 sets minimum specifications for urban and intercity charging coverage, grid integration, and load management. Table 5 shows the results.

The objectives of these standards are to provide access to charging in both urban cores (with high population density) and intercity travel routes. The policy encourages scalability and efficiency by incorporating EV infrastructure in CNG stations and allowing smart charging through time-sensitive tariffs.

Table 5
Pakistan's Infrastructure Development Framework from NEVP 2019 (MoCC, 2019; MoI&P, 2025)

Infrastructure Component	NEVP Specification	Implementation Details	Responsible Authority
Urban Coverage	At least one DC fast charger per 3×3 km grid/ 4×4 km grid	Major cities initially, expanded to secondary cities	Relevant authorities
Highway Network	Fast chargers every 15-30 km	Highway N5 and motorways M1, M2, M3, M4, M5, M9; extended to rest of country	NHA and relevant authorities
Priority Cities	Initial EV introduction and complete infrastructure	Karachi, Lahore, Rawalpindi, Faisalabad, Peshawar	City governments
Grid Integration	Smart charging for Level 2 and above	Smart metering, time-of-use pricing, innovative mechanisms	Distribution Companies (DISCOs)
Existing Infrastructure	CNG and fuel stations encouraged for charging facilities	Government bodies to encourage establishment	Government bodies
Load Management	DISCOs to identify suitable feeders	Remove supply constraints if needed for 3×3 km targets	DISCOs

3.2.3. Electricity Tariff – a defining tool

The rationalization of the EV-specific electricity tariff is the most decisive incentive in Pakistan. In Pakistan, the federal regulator, National Electric Power Regulatory Authority (NEPRA) sets end-user tariffs that are implemented by Distribution Companies (DISCOs). Considering EV charging as a separate category of consumers on the tariff schedule makes it possible for quicker grid connections and provide customized electricity pricing. EV-specific tariffs may not only define charging load profiles (e.g., time-of-use), but also have a significant impact on the OPEX of station operators and thus investment viability (Cui et al., 2023; Matkovic et al., 2024). In April 2025, NEPRA approved the rationalization of the base tariff for EVCS, reducing it from PKR 45.55/kWh to PKR 23.57/kWh and removing the previously capped operator margin of PKR 24.44/kWh, thereby allowing the market to determine charging margins. Prior to this rationalization, after inclusion of applicable taxes, surcharges, and adjustments, the effective end-user tariff had reached approximately PKR 94-95/kWh, which was considered commercially restrictive for infrastructure expansion. Under the revised framework, EVCS continues to be billed under the A-2(d) commercial category; however, monthly Fuel Cost Adjustments (FCAs), whether positive or negative, are no longer applicable to EVCS, reducing tariff volatility and improving operating-cost predictability. The decision operationalized the Federal Government's policy guidelines aimed at improving investment attractiveness and accelerating EV charging deployment nationwide (NEPRA, 2025). This reform reduces OPEX risk and, when paired with ML-based demand forecasting and DRL-based dynamic pricing, can maximize utilization and flatten load.

Figure 6 illustrates the interaction between demand forecasting, dynamic pricing, and grid management for EV charging. This enhances the study with showing how the AI-based charging strategies can be executed as adaptable, data-driven systems to enhance grid stability and efficiency in the operation of the Pakistani EV ecosystem. As shown in the figure, the ML-based forecasting module predicts approaching charging demand and grid load state and inputs the forecasts into a DRL-based pricing engine that assigns tariffs based on the predicted demand, electricity prices, and grid capacity. As shown in the figure, the ML-based forecasting module predicts approaching charging demand and grid load state and inputs the forecasts into a DRL-based pricing engine that assigns tariffs based on the predicted demand, electricity prices, and grid capacity. Such adaptive prices affect the user charging schedules, directing the shift of the sessions towards off-peak hours, which consequently affects station revenues and OPEX. This feedback of the load is returned to the forecasting model in a continuous cycle of optimization to maintain grid stability, cost efficiency, and user convenience (Cui et al., 2023; Matkovic et al., 2024; Wu et al., 2025).

Dynamic electricity pricing in empirical research shows that AI-based tariff optimization can play an important role in EV charging behavior and grid performance. Pricing models with RL have demonstrated the capability to drive the charging demand to off-peak times, alleviate the strain on peak loads, and enhance cost-efficiency of both operators and users. Simulation-based models also prove that adaptive tariff systems lead to greater system flexibility and make EV charging networks more economically viable (Cui et al., 2023; Matkovic et al., 2024; Paudel, 2023).

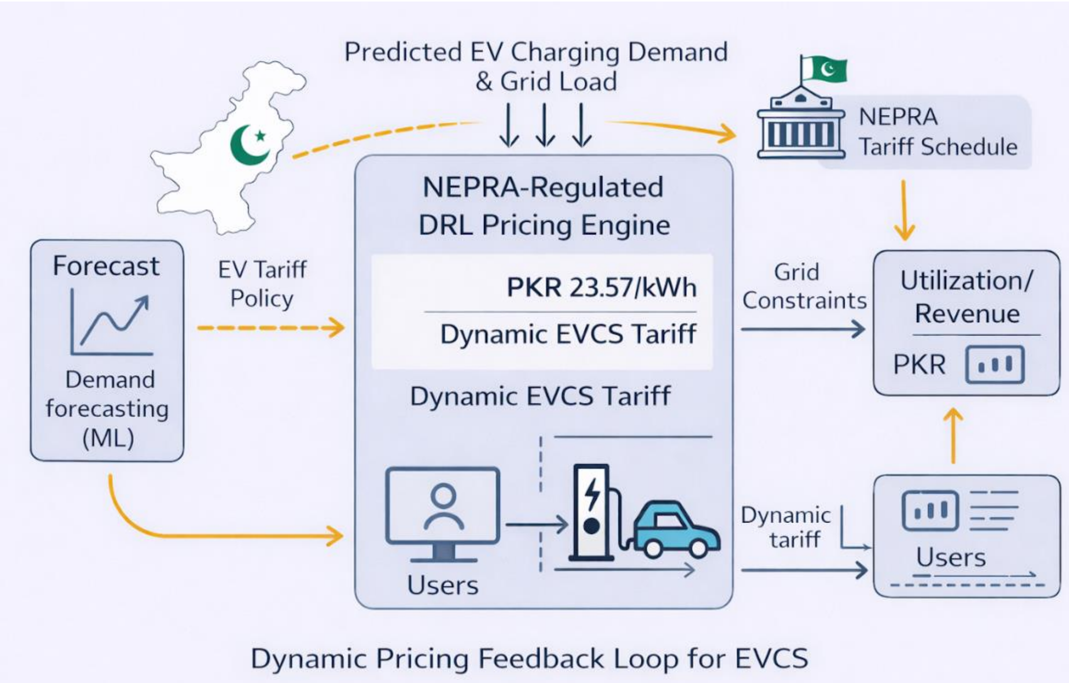


Figure 6: **Conceptual Dynamic Pricing Feedback loop for EVCS based on DRL-driven tariff optimization and demand forecasting (Cui et al., 2023; Matkovic et al., 2024; Wu et al., 2025).**

3.2.4.AI-Enabled Perspective on GoP Incentives, Policies and Planning

Although the fiscal incentives, manufacturing policies, and infrastructure structures of Pakistan are mentioned in Table 3-5, they can be enhanced by integrating AI. In the case of government incentives, the adoption probability model based on ML can be used to divide the consumers based on income, geographic location and mobility features to calculate the probability of EV adoption so that policy makers can strategically target 2W/3W and heavy-duty vehicle electrification with the highest adoption potential (Sadeghvaziri et al., 2024). Fraud detection through unsupervised anomaly detection can also stop the abuse of custom duty exemptions and tax waivers (Vanhoeyveld et al., 2020). To support manufacturing incentives, digital twin solutions can be used to virtually prototype greenfield plants and EV component supply chains to avoid costly trial-and-error during plant establishment (Yildiz et al., 2021). Predictive analytics will be able to predict battery and critical mineral demand, and AI-based recycling models will find optimal paths to recover lithium-ion cells that will strengthen the goals of the circular economy (Antony Jose et al., 2024). In infrastructure planning, GIS-based clustering and multi-objective optimization may be used to find priority corridors on which chargers should be deployed along urban grids and highways to maximize the coverage within the NEVP requirements (Li, 2025). In the meantime, deep learning models built on LSTMs can add to short-term load forecasting to EV charging demand, allowing distribution utilities to predict localized fluctuations in demand and to plan their distribution grids proactively (P., 2023). Collectively, these AI-driven solutions improve the NEVP 2019 by ensuring data-centricity, adaptiveness, and future resilience in incentives, manufacturing, and infrastructure, in addition to being policy-aligned. According to recent research in nascent energy systems, AI-based frameworks help policymakers enhance policy development and infrastructure planning in multi-scenario assessment and high-end measures by using a combination of data-based demand forecasting, spatial analysis, and economic optimization. These models have been successfully tested in EV infrastructure planning to assess policy conditions, underpin investment choices on actual demand, optimize subsidies, and promote long-term sustainability of systems (Siddiqui et al., 2025; Unterluggauer et al., 2022).

3.3. Critical Evaluation of Policy Effectiveness

Although the NEVP 2019 and the New Energy Vehicle Policy 2025-30 offer a solid framework on fiscal incentives, tariff reforms, and infrastructure targets, their success is unproven because of structural and implementation limitations, especially in infrastructure deployment, demand-supply balance, and policy implementation (International Energy Agency, 2025), while wider socio-technical shift challenges further limit the scalability in nascent EV ecosystems (Sovacool et al., 2017).

First, incentives that reduce entry barriers, including lower tariffs and tax exemptions, might not be enough to counter the high initial cost of the charging infrastructures of EVs, especially in markets with price sensitivity, such as Pakistan (Pandey, 2024; Prajapati et al., 2025). Second, the targets of the infrastructure deployment, including installing 3000 charging stations, might be inadequate in case EV adoption speeds up, causing network congestion and user loss of confidence (International Energy Agency, 2025; Mak et al., 2013). Third, private sector investment continue to be deterred by regulatory uncertainties, ambiguous business models, tariff fluctuations, and unstandardized frameworks (Statharas et al., 2019).

In addition, current policies are invested on centralized planning and tend to ignore grid constraints in real-time, regional demand changes, and renewable energy integration issues. The absence of strong monitoring and adaptive mechanisms in policy restricts further the ability to respond to the evolving market fluctuations (Fang et al., 2012; Lund, 2015; Mosavi et al., 2019).

Therefore, although the existing policies are a step towards sustainable transport, they are still not enough to guarantee 2030 goals. To enhance effectiveness, the private sector should have more involvement, regulations should be clearer, grid modernization should have more investment scope, and importantly, data-driven and AI-enabled tools should be integrated to optimize and make effective outcomes. Therefore, such adaptive and evidence-based policy reforms are important for building scalable, resilient, and sustainable EV infrastructure in Pakistan.

4. Conclusion

This paper has systematically identified ten interconnected technical, financial, regulatory, and social obstacles to the development of EVCI in Pakistan and has mapped each of the obstacles to specific AI-enabled intervention mechanisms. The study combines the findings of the SLR with the knowledge of experts to prove that the simple expansion of the infrastructure is not enough but should be accompanied by smart optimization of the location, cost, load regulation, production, and battery life cycle systems. It is revealed ML-based forecasting, RL-driven tariff optimization and charging control, GIS-based multi-objective charger placement, digital twin-enabled production and maintenance support, and AI-assisted battery health and recycling frameworks can be used together to provide grid stability, operational uncertainty reduction, better investment feasibility, and consumer trust. These data-driven mechanisms transform policy instructions into adaptive and performance-based implementation avenues when integrated in the NEVP 2019 and the New Energy Vehicles Policy 2025-30. Thus, the shift to 30% EVs by 2030 is not only a product of infrastructure rollout, but of smart integration and coordination across EVCI deployment, grid readiness, and policy execution. The study, therefore, provides a policy-consistent and scalable blueprint on AI-enabled EVCI planning in the emerging economies, in addition to Pakistan, facing grid limitations with investment and implementation constraints.

Authors Contribution

Hamza Imran: conceptualized the study, designed the methodology, and conducted the analysis
Richard Iddrissu: contributed to technical validation, review, and refinement of AI-based solutions
Shehryar Niazi: supported methodology development and literature synthesis
Marium Jalal Chaudhry: contributed to data provisioning and manuscript structuring
Azhar Ul-Haq: supervised the research and provided critical revisions

Conflict of Interests/Disclosures

The authors declared no potential conflicts of interest w.r.t. the research, authorship and/or publication of this article.

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