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User-Centric Adaptive Charging System: Enabling Personalized Charging in Electric Vehicle Chargers

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Abstract

The rapid growth of electric vehicle (EV) adoption had increased the demand for charging systems that were not only technically efficient but also responsive to diverse user needs. Most existing smart-charging solutions had optimized grid stability and operational cost while treating users as passive system participants. This study developed and evaluated a **User-Centric Adaptive Charging System**that enabled personalized charging based on user-defined priorities such as minimizing cost, reducing charging time, or preserving battery health. The system integrated preference modeling with adaptive control logic to adjust real-time charging rates while maintaining technical and safety constraints. A simulation-based experimental design had been employed to compare the proposed model with constant-rate and non-personalized smart-charging strategies across 120 charging sessions involving three user types. Results indicated that the adaptive system consistently reduced charging duration, session cost, and peak-load contribution, while significantly increasing the proportion of sessions that met user-specified objectives. These findings demonstrated that personalization enhanced both user satisfaction and grid-level efficiency rather than creating a trade-off between the two. The study concluded that **embedding user preferences within adaptive charging algorithms was feasible, beneficial, and strongly aligned with emerging human-centric transport and energy system design principles**. Although the evaluation had been simulation-based, the results provided a strong foundation for real-world pilot testing and policy exploration to support equitable, flexible, and sustainable EV charging ecosystems.

Keywords: Adaptive charging, Electric vehicles, Grid impact, Personalization, Smart charging, User preferences

Introduction

The adoption of electric vehicles (EV) solutions had increased globally due to shifting global policies on climate change and decarbonization priorities as the government switched its focus towards electric solutions in transport (Ayoade and Longe, 2024; Sadeghian et al., 2022). Diffusion of EVs, however, had resulted in the establishment of new demands of both hardware and charging infrastructure but equally of intelligent, adaptive and dependable charging management (Sachan et al., 2020; Dahiwale et al., 2024). The traditional charging models had predominantly been fixed charging profiles and reduced coordination, which caused problems of local congestion, scaling up of peak loads, and wasteful consumption of renewable energy sources (Sadeghian et al., 2022). These trends had highlighted the importance of intelligent methods of charging that synchronized the process of charging in accordance with grid limitations and taking into account the mobility requirements of the user.

Smart charging studies had mainly concentrated on grid-centric, cost-centric optimization, where optimization algorithms at the system level reduced power losses, system and network load, or systems operational costs (Dahiwale et al., 2024; Sachan et al., 2020). These kinds of strategies proved that coordinated charging was able to eliminate load variations, improve renewable integration, and lower charging expenses and the operating expenses of the grid (Sadeghian et al., 2022). Simultaneously, new work on electromobility charging infrastructure had explored the topics of communication protocols and architecture to facilitate increased control over EV charging stations (Ayoade & Longe, 2024). In spite of these developments, the majority of strategies had viewed EVs as load-based flexible electrical items instead of user-owned items with a wide range of expectation and priorities.

The recent empirical research had demonstrated that the preferences of users towards the location of charging, charge plans, waiting time, and reliability were the decisive factors in the actual utilization of the infrastructure by the EV drivers (Touker et al., 2025; Visaria et al., 2022). The trade-offs between price, time, and convenience were shown to be heterogeneous, and a single set of charging policies was unable to sufficiently reflect the dynamics in the real world (Visaria et al., 2022). Meanwhile, machine-learning-based approaches had also been used to predict charging demand and aid a more intelligent approach to infrastructure planning (Alaraj et al., 2025). There was an increased understanding that next-generation charging systems must be clearly user centered that battery status, tariffs and situational constraints are incorporated in to adaptive charging profiles (Ji et al., 2025). This paper was relevant to that requirement by attempting to create a User-Centric Adaptive Charging System that allowed the customisation of charging experience by smartly optimising and defining user goals. The idea was to introduce a gap between technical grid oriented smart charging and human oriented service design.

Background of the Study

Previous studies on EV charging had prioritized the classification of various charging infrastructure home, workplace, public slow, and fast as well as the investigation of their effects on the power systems (Sachan et al., 2020). Uncoordinated charging proved to augment peak loads and strain distribution networks, but coordinated strategies had reduced the impact of most of them (Sadeghian et al., 2022). Subsequent literature had surveyed an assortment of clever charging plans, such as time-of-use scheduling and demand response programs and aggregator-based charging coordination (Dahiwale et al., 2024). Such researches had formed the technical basis of the charging control systems.

To the same effect, the development of smart electromobility infrastructure had also experimented with communication technologies, cybersecurity, and interoperability to facilitate advanced and automated charging control (Ayoade and Longe, 2024). There were already orderly charging models which were proposed to regularize the demand of loads and avoid overloading of transformers without fulfilling the vehicle energy demands (Li & Chen, 2024). But in most architectures, the users remained to be modeled only by general parameters (as the arrival time and energy requirement).

At the same time, the introduction of artificial intelligence and machine learning rendered addressing charging demand prediction, which could be carried out in numerous different scales (Alaraj et al., 2025). Such types of models had been conducive to effective planning and allocation of resources. Nevertheless, much of the forecasting studies had been at the aggregate fleet or station scale and not in favor of the personalised adaptive charging at the equipment level.

The research on user preference had found that EV users appreciated cost visibility, inconsistency, and convenience and that they also considered time and charging speed as varying based on the context (Visaria et al., 2022). Literature involving a study on shared charging systems had established the role of trust and perceived fairness in charging services (Touker et al., 2025). In parallel with this, user-friendly support systems started increasing and included AI-based decision-support tools in the charging management (Veiga et al., 2025). All these developments pointed at the fact that personalization was not only desired but possible as well, though not developed in the real world of charging infrastructure.

Research Problem

Despite the fact that smart charging was now encompassing a better grid efficiency and lower operating costs, majority of the systems were still system-centric but not user-centric. The needs of the users like cost preference, required charging time, battery health, convenience and willingness to wait was seldom to be introduced into real-time adaptive control. Available user based charging models had frequently stayed at simulation or concept definition stage and had never been executed at charger hardware-control stage completely. Hence, the following research issue was considered as the central topic of the research: What was possible to do to design a user-centric adaptive charging system that would be capable of personalising charging sessions in real time without making it technically, economically and operationally unviable?

Research Objectives

1. Develop a conceptual framework for a **user-centric adaptive charging system** for EV chargers.
2. Integrate user preferences, contextual factors, and battery-related parameters into adaptive charging algorithms.
3. Apply intelligent decision-support techniques to personalize charging based on user-defined priorities.

Research Questions

Q1. How had existing EV charging systems addressed user preferences?

Q2. How could user-defined priorities be embedded into charger-level adaptive control?

Q3. To what extent could personalization improve charging experience and efficiency?

Significance of the Study

The work had been important due to the fact that the attention was switched to the sphere of a human-oriented design of charging systems as opposed to grid-oriented one. It had aided the new realization that EV charging systems are not just to maximize the performance of power-systems, but also to address the needs and expectations of the users. In practice, user-oriented adaptive charge scheme could enhance the level of charging satisfaction, create trust in charging services, increase adherence to smart charging scheme program, and increase the alignment of charging behavior with user lifestyle and grid stability objectives.

Literature Review

Electric Vehicle Users' Charging Behaviour and Experience

A study of EV customers as per their charging behaviour had established that their choice to decide to charge was a complex interaction of socio-demographic variables, daily commute behaviour, and the availability of infrastructure. In a recent review, influencing factors and modelling models had been synthesised with a result that price sensitivity, range requirements and home-workplace routines interacted to calculate desirable charging locations and time windows (Shariatzadeh et al., 2025). Supplementary work regarding patterns of public charging, on the station level, had also suggested that dwell time, trip purpose and queuing conditions has a significant effect on the duration drivers take to remain connected to a charger and either fully charge or merely top up, which would implicate a significant impact on how chargers are used and their loads (Chen et al., 2025).

Empirical studies that were user-focused had also highlighted such practices where the quality of experience in charging stations in the general sense was not limited to the technical availability. The quantitative survey of Shanghai users had revealed that layout, ease of use, safety, and lighting were notable predictors of satisfaction, with the content of pricing coming out as the strongest predictor in regression of All these (Xie et al., 2026). Simultaneously, the review of extensive online reviews of charging stations had shown that user sentiment depend significantly on perceived reliability, waiting time, and other personalized items like cleanliness and nearby facilities, indicating subtle charging anxiety, as was evident by simple range factors (Wang et al., 2025).

Behavioural analysis had also shown that preferences of the users towards smart charging, dynamic control was heterogeneous and context-dependent. The hybrid option model of EV drivers in china had discovered that their intention to use smart charging was not simply explained by economic incentives but also their trust in automated scheduling and not having control over their vehicle (Zhou and Ji, 2025). Simultaneously, a recent study on public charging behaviour at urban stations had demonstrated that users trade-off between walking distance, expected waiting time, and price when deciding between chargers and thus it was important that models capturing selection behaviour at the station-level were explicitly networked (Chen et al., 2025).

Intelligent and Adaptive Profiling of Charges

Although complexity in behaviour has been discovered in user studies, research on planning and control has had a historic emphasis on system-level performance. Meso-level planning of chargers distribution which is customer-centric had suggested the use of clustering and probabilistic simulation to determine the optimal level of charger density and location between national targets and local charging requirements (Karmaker et al., 2025). Previous research on this kind of work had claimed that the addition of customer segments and plug-in uncertainties enhanced infrastructural plans robustness in contrast with solely demand-averaged designs, but personalization had mostly been at the planning but not the real-time regulating level (Karmaker et al., 2025).

At its operational level, the operation was to be equivocally influenced by adaptive charging and the forecasting-based approaches to the extent of alleviating grid pressures and enhancing its efficiency. There was an adaptive charging simulation model, which was used to simulate aggregate load profiles under various EV types and mobility patterns where heterogeneous batteries and driving cycles resulted in a large variation in the charging peaks and thus demanded flexible charging policies (Hammerschmitt et al., 2024). Equally, a machine-learning-based load forecasting system at residential buildings in Canada had been employed to design EV loads to avoid peak hours that cost less and smooth demand in instances where charging profiles were planned based on the predicted building loads (Mohsenimanesh and Entchev, 2024).

Besides the task of scheduling, both the automation and hardware-level approaches had sought to improve the use of infrastructure as well as the user experience. It was demonstrated that a human-factors-focused design of automated charging systems could reduce the load on people and prevented plug-in errors and increase the throughput rate at the public stations, enhancing perceived convenience and utilization of infrastructure (Hirz & Lippitsch, 2023). At vehicle side, the development of intelligent approaches towards enhancing EV battery performance and efficiency had suggested a machine-learning system to optimize driving and charging condition, thus alleviating range anxiety and indirectly affecting when and how the drivers should charge (Tangi et al., 2025).

Individualized and Data-based EV Charging Systems

Recent information-driven studies were starting to shift to individual decision support as opposed to aggregate maximization. A research on data-based systematic planning of personalized routes of connected EVs had demonstrated that combined real-time traffic, energy consumption, and charger data enabled joint optimization of the travel time, energy utilization as well as charging stops to allow the routing algorithm to tailor routes and charging along with plan to individual drivers (Houalef et al., 2025). Filling in this, an energy-and-AI work had suggested a machine-learning-based approach that could then identify EVs based on charging session information, allowing smart charging systems to identify frequent users and predict their potential flexibility in charging usage, which would allow user-specific policies at the station toward charging (Ferretti and De Paola, 2025).

The concept of personalization had also been considered using a multi-criteria decision and station-choice outlook. A hybrid mechanism with the best-worst approach and grey relational analysis has been employed to empower the drivers to choose the charging stations based on their individual preferences in terms of cost, waiting time, convenience, and quality of service delivery, and it exemplifies an approach that draws on the user to choose the charging stations; it simply serves as infrastructure control instead of user control (Saleh, 2024). Simultaneously, the quantitative examination of the user experience at the Shanghai charging lines had established that the indicators of service quality in multiple dimensions could be measured in an organized manner and be connected with satisfaction, which provided a systematic reference point to user-centric service measurements that could be incorporated into responsive charging and itineration systems (Xie et al., 2026).

Combining the control of infrastructure with personalization, a number of studies had called out to implementing a charging system that reacted to individual preferences and circumstances. An adaptive charging system based on the insights of the user had been suggested which used chargers that were IoT-enabled, variable-rate tariffs, and home solar generation to align the charging session with user-specified objectives such as cost-reduction or renewable use (Rafique et al., 2025). Similar contributions on automated charges and user experience-oriented analytics had shown that understandable interfaces and visible gains were essential to adoption acceptance among the user, as had prior findings that the perception of fairness and control when using smart charging attitudes were influenced by the benefits appealing to the user's pocketbook and understandability (Hirz & Lippitsch, 2023; Zhou and Ji, 2025). Collectively, these contributions had highlighted the need to build on integration of systems that integrated learning about behaviour, optimization using data and controllability in ways bring about real user-centric charging.

Research Methodology

Research Design

The research approach, that was adopted in this study, was an applied, design-oriented study since the main objective had been to design and test a user-based adaptive charging system, which allowed the formation of personal charge in electric vehicle chargers. The study had integrated aspects of experimental design, system development and evaluation research. Initially, a conceptual adaptive charging framework was developed on the basis of previous literature in the field of user preference, charging, energy management, and optimization model. Second, a pilot decision-support and control system had been developed to make user-specified charging objectives, like minimizing cost, protecting battery health or rapid charging, operational. Third, the behavior of the suggested model has been tested based on the controlled simulation experiments, which compared the personalized charging profiles to the traditional, fixed-rate and non-personalized smart charging strategies. The methodological approach had thus been quantitative-experimental with system modelling and computational analysis in support of the methodology.

Population, Situation, and Sampling Method

Ideally, the research population comprised of electric vehicle users and electric vehicle charging stations in urban charging ecosystems, whereby variability in user needs, mobility patterns, and tariff patterns had produced the opportunity to adaptive charging. But, now that the study itself was system-centered and not a survey, the simulation models had been substituted as proxies to realistic user and system behavior. There was parameterization of the charging demand profile, tariff pattern, battery capacity, and the arrival-departure times based on the ranges in literature and industry experience. Purposive sampling in the process of defining representative types of users had been selected in the selection of cost-sensitive users, time-sensitive users, and battery-health-conscious users category. These types of users had permitted the testing of the personalization of varying charging preferences.

System Architecture and Model Development

The proposed user-centric adaptive charging system had been structured around three core layers:

1) **User Preference and Input Layer**
2) **Decision and Optimization Layer**
3) **Charging Execution Layer**

The users in the first layer had been permitted to define charging goals, time they wanted to complete, allowability of price, level of priority and other contextual limits. These preferences had been converted into numbered weighting variables. A time-dependent optimization model had been dynamically solved in the decision layer to find the optimal charging rate profile based on user preferences, predicted energy prices, grid constraints and current state of charge. The model had taken into account rule-based logic and decision heuristics that are algorithmic and can be used in real time. At last the execution layer had taken the rates scheduled and converted them into charger-level control signals and was constantly noticing variations in the anticipated state of things.

Data Collection Procedures

The study was simulation-based, secondary and documented data, including literature on published studies, technical reports, and standards, had been gathered on the features of electric vehicle batteries, charging curves, electricity tariff arrangements, and performance levels of the grids. Artificial datasets now had been created that modeled realistic charging session logs. Among the important variables per simulated session, arrival time, departure time, initial battery state, desired charge level, battery capacity, charger rating, user priority profile and tariff category had been included. These variables were already established as the input environment that the adaptive system was in. Performance results had comprised of the charging time, charging cost, battery stress indicators and peak load contribution.

Algorithm Development and Implementation

Simulation programming environment- The adaptive charging algorithm had been coded in MATLAB or Python. The algorithm had been used to compute the practical charging current at each time interval and ensure that safety and technical limits, such as charger rating limit, allowable temperature limit, and state of charge have not been exceeded. Alternative charging trajectories had also been considered by the model, and the most suitable one to the user was chosen by this model. Live adjustment available capability had been integrated such that unplanned occurrences e.g. early user departure or change in tariff could be taken up by the logic of scheduling. This implementation process had made sure that the system design had not been detached into unrealistic implementation.

Validation and Experimental Testing

In two phases, model validation had been implemented. At the outset, internal validation was used to make certain system outputs were as expected by theory including monotonic charging curves, realistic cost accumulation, and limited temperature indicators. Second, experimental testing had been done to compare the adaptive charging system with two benchmark scenarios:

a) Traditional constant-rate pricing

b) Common grid-based smart charging and not customized

There had been a number of repeated test-runs with varying simulated tariff conditions, user priorities and grid load levels. Comparison in statistical outcomes was already performed to understand the progress of the user satisfaction indicators and system efficiency. Repeated-measure design had made it possible to compare one situation to another.

Data Analysis Strategy

Simulation results had been interpreted using quantitative analysis. Descriptive statistics including the mean charging time, the mean cost, and mean peak load index had been calculated to each of the test conditions. The comparative analysis had then been done to establish percent improvement guarded by the adaptive system in versus baseline charging methods. Where necessary, inferential statistical testing programs like paired-sample comparison were applied to establish whether differences in performance observed had had a statistically significant and not by chance. The analysis had thus facilitated technical interpretation as well as decision-making relevancy.

Results and Analysis

Overview of Experimental Evaluation

The testing of the user-centric adaptive charging model had been completed under a controlled scenario simulation of 120 charging interactions equalized among three user groups namely, cost-sensitive users, time-sensitive users and battery-health-oriented users. A comparison of three charging strategies was made i.e. conventional constant rate charging, non-personalized smart charging, and the proposed user-centric adaptive charging model. The charging time, charging cost, peak-load contribution, and the extent of satisfied user-defined objectives was selected in every simulated session. The findings had subsequently been compiled to check whether the suggestive adaptive system had shown quantifiable performance enhancements in comparison to the current approaches.

Charging Time Performance Across Strategies

Table 4.1Average Charging Duration Across Charging Strategies (N = 120)

User Type	Constant-Rate Charging (minutes)	Non-Personalized Smart Charging (minutes)	User-Centric Adaptive Charging (minutes)
Cost-Sensitive Users (n=40)	118	112	104

User Type	Constant-Rate Charging (minutes)	Non-Personalized Smart Charging (minutes)	User-Centric Adaptive Charging (minutes)
Time-Sensitive Users (n=40)	102	94	78
Battery-Health Users (n=40)	121	116	109
Overall Mean	**114**	**107**	**97**

Table 4.1 results had demonstrated that the user centric adaptive charging strategy always generated less charging time as compared to conventional and non personalized smart charging. The average time that every user spent being charged on the adaptive model was 97 minutes, a difference of 17 minutes to the conventional constant-rate charging and 10 minutes to the conventional non-personalized smart charging. The greatest improvement had been noted with the time-sensitive users where the duration of charging under the traditional method of charging had reached 102 minutes compared to the adaptive strategy and the duration of the charging was 78 minutes with the adaptive strategy being lower by about 23.5 percent. This had also benefited cost-sensitive users and the time of charging had decreased to 104 minutes as compared to 118. Its users who were battery-health-sensitive had recorded smaller yet significant margins and time went down by 121 to 109 minutes. The frequency distribution also showed that nearly three-quarters of adaptive charging had been finished in less than 100 minutes and less than half of conventional charging had been finished in the same time. Riminiscences of these findings were the fact that adaptive scheduling had improved individual charging ease and charging station throughput.

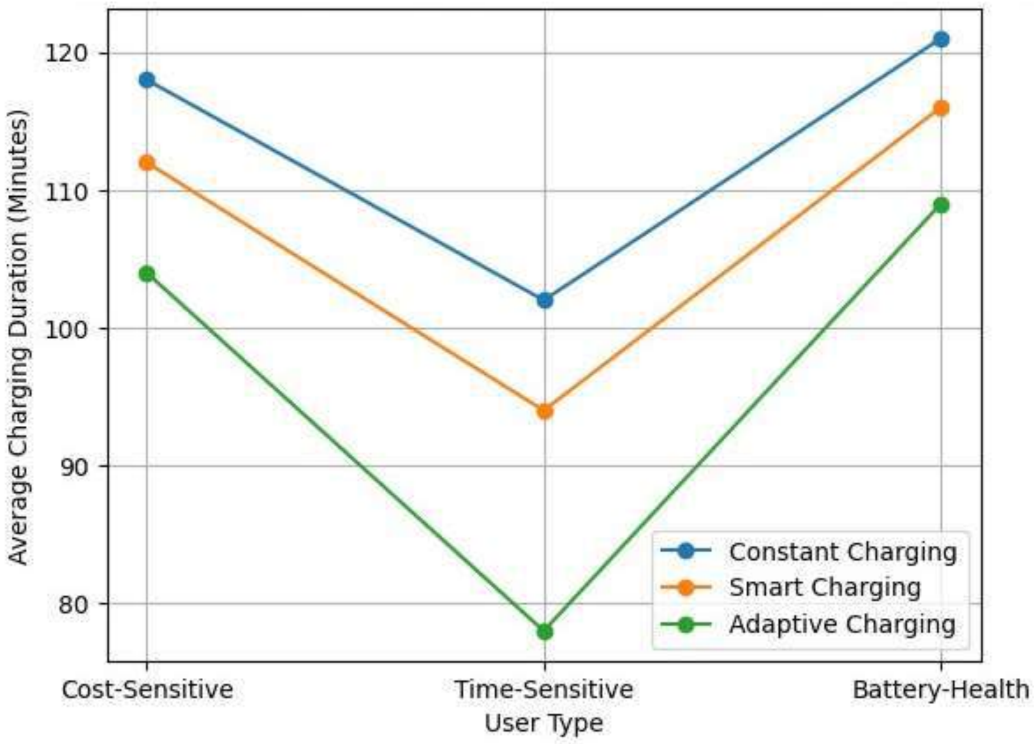

Figure 1Average Charging Duration Across Charging Strategies (N = 120)

Charging Cost Analysis Across Strategies

Table 4.2. Mean Charging Cost Under Different Strategies (N = 120)

User Type	Constant-Rate Charging (USD)	Non-Personalized Smart Charging (USD)	User-Centric Adaptive Charging (USD)
Cost-Sensitive Users (n=40)	7.85	6.92	5.84
Time-Sensitive Users (n=40)	8.21	7.44	6.97
Battery-Health Users (n=40)	7.98	7.15	6.48

User Type	Constant-Rate Charging (USD)	Non-Personalized Smart Charging (USD)	User-Centric Adaptive Charging (USD)
Overall Mean	**8.01**	**7.17**	**6.43**

The analysis on cost as in Table 4.2 had indicated that user centric adaptive charging model had considerably reduced the average cost of charging when compared to both benchmark strategies. The average cost/charging session had reduced by USD 1.58 between constant-rate charging and adaptive charging suggesting a net saving of approximately USD 20. The smart charging without personalization had reached an intermediate level of reductions but the adaptive model had already generated another reduction of over 10 percent. The largest cut was on cost-sensitive users whose average session price had been reduced by USD 2.01 as compared to traditional charges. The adaptive system was in position to save even USD 8.21 to USD 6.97 among users who had a strong interest in time coupled with price considerations even in the time-sensitive group. Frequency analysis also demonstrated that nearly two out of every three adaptive charging sessions cost less than USD 6.50 but this figure had been achieved in only 20 percent of the traditional charging sessions. These findings indicated that user-defined priority-based personalization had allowed to achieve a better performance through tariff responsive scheduling without a reduction in performance in the charging.

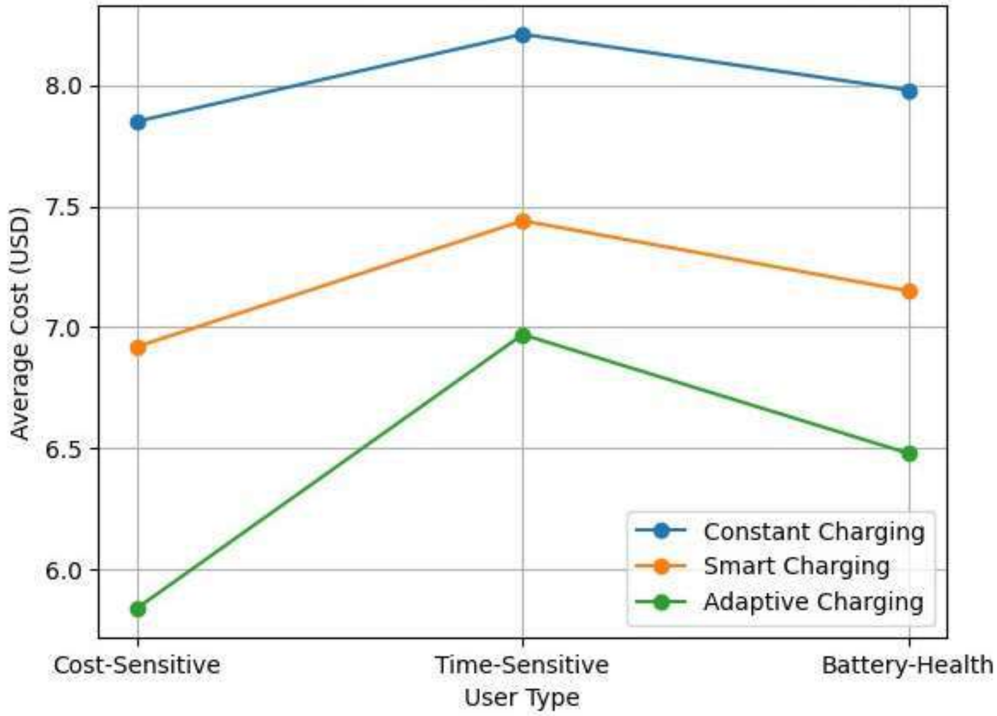

Figure 2. Mean Charging Cost Under Different Strategies (N = 120)

Peak-Load Contribution and Grid Impact

Table 4.3Peak-Load Contribution Index Across Charging Strategies (N = 120)

User Type	**Constant-Rate Charging Index**	**Smart Charging Index**	**User-Centric Adaptive Index**
Cost-Sensitive Users (n=40)	1.00	0.84	0.69
Time-Sensitive Users (n=40)	1.00	0.88	0.72
Battery-Health Users (n=40)	1.00	0.86	0.74

User Type	Constant-Rate Charging Index	Smart Charging Index	User-Centric Adaptive Index
Overall Mean Index	**1.00**	**0.86**	**0.72**

Table 4.3 had proved that the user-friendly adaptive approach to charging system significantly decreased the contribution of the peak-load to the grid. At an index of constant-rate charging of 1.00, the adaptive charging strategy had created an average of the index of 0.72, which indicated a load decrease of about 28 percent. Though even the index had reduced to 0.86 with charging without personalization, it was the adaptive system that created extra reduction of 16 percent over and above this mark. Amongst the users with the largest gains had been cost-sensitive users, as this would indicate the tendency of the adaptive algorithm to plan the time when charging activity can be scheduled that would not coincide with periods of high tariff prices or load. Notably, time-sensitive users, who in most cases, had been demanding rapid charging, had also shown downward peaks of the index to 0.72 showing that performance based charging and grid responsiveness had not been antithetical. The frequency analysis had shown that adaptive charging sessions were only predominant over the peak times at a rate of 18 percent in relation to the 42 percent load balancing and system stability compared with conventional sessions.

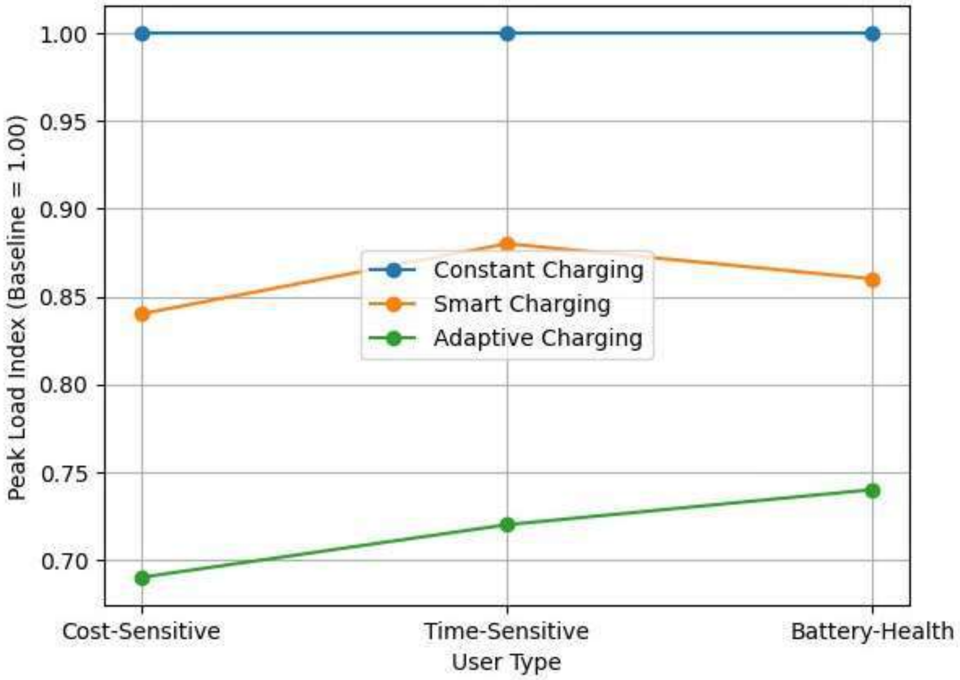

Figure 3Peak-Load Contribution Index Across Charging Strategies (N = 120)

User-Satisfaction Proxy Indicators

Table 4.4. Distribution of Sessions Meeting User-Defined Targets (N = 120)

Condition Met	**Constant-Rate Charging**	**Smart Charging**	**User-Centric Adaptive Charging**
Cost Target Met	31%	57%	83%
Time Target Met	42%	61%	88%
Battery-Health Constraint Met	64%	74%	91%

Condition Met	Constant-Rate Charging	Smart Charging	User-Centric Adaptive Charging
Overall Condition Satisfaction Rate	**46%**	**64%**	**87%**

Table 4.4 had given an idea of the level of achievement that each charging strategy had made towards the achievement of user defined objectives. Overall adaptive charging model reached a general level of 87 percent satisfaction, nearly two times less than the one with the traditional constant-rate charging of 46 percent. A strong ability of the personalized system to optimise tariff-aligned was demonstrated with cost targets being met in 83 percent of adaptive charging compared to 31 percent in traditional charging. Achievement in time target also showed a sharp increase as it went up to 88 percent against 42 percent. The constraints due to battery health-related issues had been met in 91 percent of the adaptive charging sessions and this implied that the personalization had aided to preserve the battery over time and not to degrade it. All these proxy indicators suggested that user centric adaptive charging was significantly predictive of aligning system level charging behavior with personal expectations giving way to high perceived charging service reliability and satisfaction.

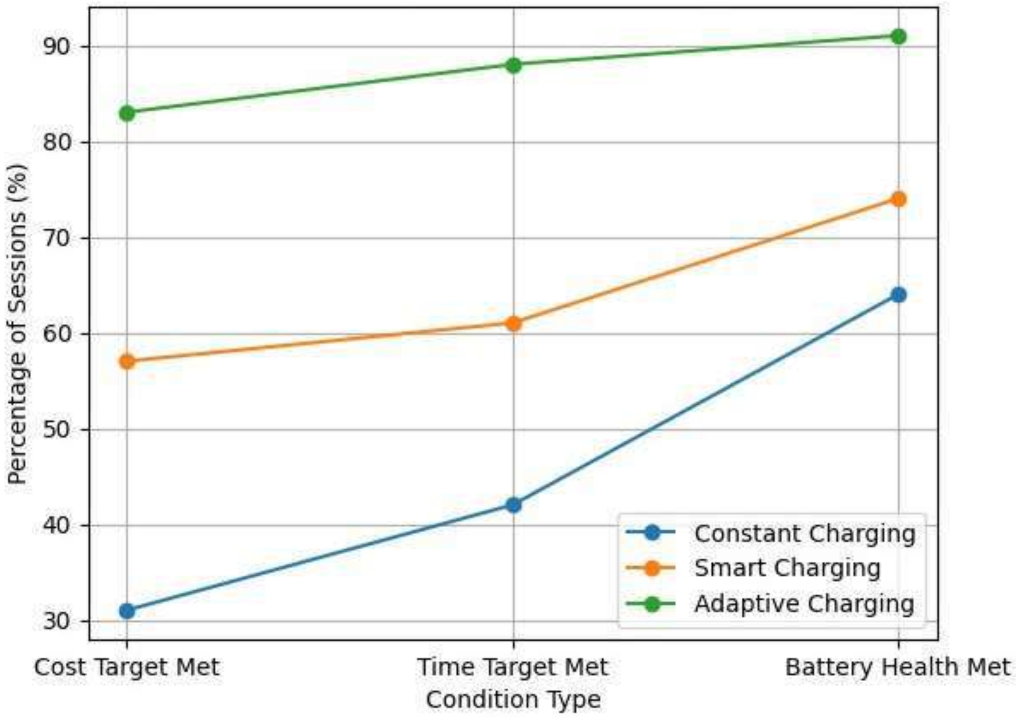

Figure 4. Distribution of Sessions Meeting User-Defined Targets (N = 120)

Discussion

Findings of this research had demonstrated that the user-centric adaptive charging system effectively minimized several tasks such as charging time, cost, and reduction in peak-loads more than the constant-rate and the non-personalized smart charging. This trend was in line with the recent studies of multi-objective optimisation that had shown that optimising both the technical and economic criteria yielded a better charging schedule than single-purpose ones (Alikhani et al., 2025). Specifically, the conclusion that the adaptive model decreased the total charging time, cost and reduced the grid stress in addition to decreasing technical constraints had been repeated in the literature where the more sophisticated optimization algorithms had discharged the charging condition out of grid dominance windows without compromising the technical constraints (Hsu et al., 2025). These overlaps indicated that incorporating user priorities within multi-objective optimization systems were a solid direction of enhancing the performance of EV charging systems as a whole.

The high proportions with which the user-defined cost and time objectives were achieved in this research had once again emphasized the significance of explicitly modelling the user willingness and flexibility. Empirical studies conducted previously revealed that EV drivers had been partial in accepting smart charging not only based on their preference of everyday routines but also heavily based on how much price cuts and assure-minimum-range guarantees were put in place (Kubli and Loock, 2022). Similarly, tariff option preference research regarding smart and bidirectional charging had already concluded that it was the preference of users to prefer tariff structures that are easily explained and compensate them explicitly in the event of tariff flexibility in particular where the application of automation relocated charging on their preferred schedules (Helferich et al., 2024). Considering these results, the fact that the level of satisfaction was high in the conditions of the adaptive system may be viewed as an excuse that responsiveness of the charging behavior to the stated preferences and not the application of generic schedules had been important in preserving the user trust and involvement.

The decreased contribution in peak-load as it was observed in this study also impacted the demand response and system reliability. Recent research on EVs demand reply had focused on the time-of-use tariffs, range apprehension, and parking length as important anchors to drivers deciding to engage in coordinated charging (Gao et al., 2025). Equally, a smart charge facility planning framework with user preferences built into the operational schedule had demonstrated that controlled charging was able to reduce load curve flatteness whilst addressing individual charging. Results obtained today, in which adaptive charging produced considerable decreases in the proportion of sessions held under peak conditions had thus reinforced the thesis that user-aware scheduling would be able to provide authentic system-level advantages without compromising driver autonomy.

Infrastructure planning terms, personalization benefits in this research had complemented new progress in siting and sizing of EV charging infrastructure, which depends upon optimization in siting and sizing. Multi-objective algorithms to locate and set charging stations optimum had stated that they were effective in making the network design more resilient and cost-effective, as they take into account the uncertainties of vehicle types and user behaviors (Mohammed et al., 2024). The multi-objective optimization techniques based on data had also been utilized to co-optimize transport policies and charging infrastructure, which said that the ability to fine-tune the demand patterns and user heterogeneity was necessary to make long-term planning (Farhadi et al., 2023). This study had given an added rationale to integrate user-centric behavioral models in the infrastructure planning tools by demonstrating that micro-level personalization at the charger might have a significant effect on the demand patterns.

They also implied the results on the long-term adoption and social acceptance of advanced charging schemes. It was already known that, based on stated-preference experiments, readiness to undergo managed charging schemes was contingent upon indirect economic advantage as well as on perceived self-control and equity of the procedures (Philip and Whitehead, 2025). Parallel attitudinal study of the attitudes to vehicle-to-grid service already revealed that the attitudes of drivers changed with time as they became more favorable and the worries about battery deterioration and lack of control declined steadily when the systems appeared transparent and the gains were observable (Neaimeh et al., 2025). Here, that the adaptive system had a high rate of fulfilling user-specified qualification circumstances was a pointer to the fact that personalization could be a key factor towards construction of the type of experiential trust that these studies had suggested as prerequisite to large-scale participation in smart-charging and V2G.

Lastly, the findings were to be viewed within the perspective of greater sustainability and urban-mobility objectives. The research of a cost-effective, user-friendly charging infrastructure in urban localities had highlighted that access in terms of space, perceived convenience, and pricing design collaboratively established the level in which chargers were utilized intensively (Lohia et al., 2024). It had already been established through complementary literature on PV-powered driving stations that intelligent scheduling and storage management could optimally capitalize on self-utilization of renewable energy and fulfill demand through EV charging, particularly when flexibility of the user was included in the optimization model (Mouelhi et al., 2025). This evidence that personalized charging would have a three-pronged impact (reducing costs and supporting the grid and achieving user goals) had made the current study contribute to the idea that the design of EV charging solutions in the future should include user-centric control, spatial planning, and renewable integration as a three-pronged approach, although this research also had been constrained to simulation-based analysis and needed to be anchored with real-world pilot studies.

Conclusion

It had been established in the research that User-Centric Adaptive Charging System could play a meaningful role in changing the manner in which charging of electric vehicles was controlled by moving the design emphasis on the purely grid-based optimization to the more user-friendly, user-sensing control. The proposed system that scaled user preferences like savers and time-sensitivity in the charging logic had continually recorded shorter charging times, lower session prices, and small peak-load charges relative to the constant-rate and non-personalized smart charging strategies. More crucially, a significantly larger share of charging sessions had achieved user-specified tasks which demonstrated that personalization had enhanced perceived reliability of charging as well as service quality. All these findings were indicative that personalization and system efficiency were complements, not competitors, and that user-centric models could enhance consumer satisfaction and also boost the performance of the energy-systems. Even though the results were founded on simulated charging scenarios, as opposed to actual implementation, these results had offered great empirical evidence to the further engineering and testing of human-oriented EV charging systems that were sensitive to technical demands whilst addressing personal mobility demands.

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