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A Study on the Influence Mechanism of User Demand Response and Service Experience in Urban New Energy Charging Market Based on Multi-model Fusion: A Case Study of Urumqi

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Abstract: To address the rapid expansion of the new energy vehicle market and the challenges it poses to urban charging infrastructure, this study takes Urumqi as an example, aiming to deeply analyze user charging behavior engineering and the core influence mechanisms of charging service satisfaction in the new energy charging market. Based on an analysis of 978 valid user questionnaires and using multiple linear regression, K-prototype clustering, structural equation modeling (SEM), and random forest models, the research constructs a multi-dimensional and multi-level integrated analysis framework. The findings indicate that the rational distribution of charging stations (β=0.249) and charging speed (β=0.247) are the primary factors influencing user satisfaction, with their importance surpassing that of charging costs. User groups can be clearly classified into three types: "high-frequency practical users," "price-sensitive users," and "tech enthusiasts," with significant differences in charging behaviors, technology preferences, and policy attitudes among them. Additionally, the random forest model identifies that public expectations for the market outlook (feature importance: 63.6%) and perceptions of the speed of charging facility construction (feature importance: 30.3%) are the key psychological drivers of support for new energy policies. By quantifying the impact paths and weights of these key factors, this study reveals the central contradictions in the current urban charging market and the heterogeneous needs of user groups, providing scientific data support and decision-making references for optimizing charging network planning, formulating precise operational strategies, and enhancing policy effectiveness.

Keywords: New energy vehicles, Charging facilities, User behavior, Satisfaction model, Multi-model integration.

1. Introduction

Driven by the global energy transition[1] and the "dual carbon" strategic goals[2], the new energy vehicle (NEV) industry[3] has become the core engine for promoting green and low-carbon development in the transportation sector. As a crucial pillar for the widespread adoption of NEVs, the planning, construction, and operational efficiency of charging infrastructure are directly linked to user experience and the industry's market prospects. Urumqi[4], as a major central city in Northwest China and a key node in the "Belt and Road"[5] initiative, is witnessing explosive growth in its NEV ownership, creating a tremendous and urgent demand for charging services[6]. However, there is a significant disconnect between the rapidly expanding market demand and the still-developing infrastructure network, manifesting in issues such as uneven distribution of charging stations[7], inconsistent service quality, and low operational efficiency. These problems have become bottlenecks restricting the healthy development of the local NEV industry[8]. Therefore, conducting a scientific and systematic analysis of the current state of the charging market[9], user behavior patterns, and influencing factors of charging service satisfaction holds important theoretical and practical significance.

Existing research mostly focuses on the macro-level planning and layout of charging facilities, technical standards, or single-market analyses. Some studies examine individual factors influencing users' charging choices—such as charging prices and range anxiety—but often rely on traditional descriptive statistics or single regression models[10], making it difficult to uncover the complex interactions and deep causal relationships among multidimensional factors. In addition, current research generally lacks a systematic exploration of heterogeneity of charging user groups in demand and behavior [11] and tends to treat users as a homogenous whole. This makes it challenging to achieve precision and differentiation in policy-making and marketing strategies[12], especially when differences in users' technological acceptance, consumer habits, and policy perception are overlooked. The limitations of this research perspective leave our understanding of the complete "infrastructure construction–user experience–behavioral feedback–policy support" closed-loop incomplete.

To address these research gaps, the core contribution of this paper lies in constructing and applying an integrated analytical framework based on multi-model fusion, enabling in-depth insights from "prediction" to "decision-making." First, this study innovatively combines multiple linear regression[13], K-prototype clustering[14], structural equation modeling (SEM)[15], and random forest models—bringing together various machine learning and statistical techniques—to systematically identify the key drivers of user satisfaction and quantitatively map their impact paths and weights. Secondly, through clustering analysis of multidimensional data such as users' charging behaviors, technological preferences, and social attributes, the study accurately profiles different user groups and uncovers the market's heterogeneous structure. Finally, this paper not only focuses on user satisfaction but also further explores the deeper psychological factors influencing public support for new energy policies, achieving a cross-level analysis from micro-level user behavior to macro-level policy perception.

2. Methods

2.1. Data Source and Pre-processing

The data for this study mainly comes from a large-scale online questionnaire survey and in-depth offline interviews targeting new energy vehicle owners and potential consumers in Urumqi. The survey was designed based on the 4P4C integrated marketing theory, covering five dimensions: market supply and demand, user behavior, policy drivers, technology acceptance, and facility optimization. Data was collected from December 2024 to January 2025, with over 1,000 questionnaires recovered. After data cleaning, eliminating questionnaires completed too quickly, those with logically inconsistent answers, or significant missing information, a total of 978 valid samples were obtained. To ensure the reliability and validity of the questionnaire, a pilot survey was conducted before the formal investigation, and the quality of the questionnaire was tested. Reliability analysis showed a Cronbach's α coefficient of 0.954, indicating excellent internal consistency. For validity, the KMO value was 0.979 and the Bartlett's test of sphericity was significant ($p<0.001$), demonstrating a clear data structure highly suitable for subsequent statistical modeling such as factor analysis, thus providing a solid data foundation for in-depth analysis in this study.

2.2. Identification Model for User Satisfaction Factors

To identify and quantify the key factors affecting users' satisfaction with public charging facilities, this study employed a multiple linear regression model. This model effectively analyzes the linear relationship between multiple independent variables and a single dependent variable. In this study, users' overall satisfaction with public charging facilities (measured on a 1–5 Likert scale) was set as the dependent variable. Independent variables covered a range of dimensions, including core charging services (e.g., charging speed, charging fees), facility availability (e.g., rational distribution, facility safety), user experience issues (e.g., charging pile damage, occupation by fuel vehicles), and operator types. By constructing a regression equation, the model can accurately estimate the independent contribution of each variable to satisfaction (i.e., regression coefficient), and test its statistical significance, thus scientifically screening out the most important driving factors.

2.3. User Segmentation Model

To reveal the internal heterogeneity of the new energy vehicle owner market in Urumqi, this study used the K-prototype clustering algorithm for market segmentation. Traditional clustering algorithms (such as K-means) can typically only handle numerical data, whereas the user data in this study includes mixed data types: numerical (e.g., income level) and categorical (e.g., occupation, vehicle model). The K-prototype algorithm combines the strengths of K-means and K-modes, enabling effective clustering of mixed data types through a comprehensive distance measurement function. In this study, 21 mixed indicators involving user charging behavior, technological preferences, social attributes, and policy attitudes were selected as clustering variables, aiming to group users with similar characteristics, thereby forming distinct user profiles with varied needs, providing a basis for subsequent precision marketing and personalized services.

2.4. Multi-dimensional Impact Mechanism Analysis Model

To explore the complex multi-path impact mechanisms among charging facility construction, service experience, and user behavior, this study constructed a Structural Equation Model (SEM). SEM is a powerful statistical method that allows simultaneous handling of both observable and unobservable latent variables, and can test complex networks of causal relationships between variables. This model, based on the Technology Acceptance Model (TAM) and public service satisfaction theory, set up latent variables such as "Technological Foresight," "Basic Services," and "Policy and Environmental Support," each measured by a set of observable indicators (e.g., questionnaire items). By constructing a path diagram, SEM not only verifies the direct and indirect relationships (i.e., mediation effects) between latent variables, but also provides overall model fit indicators (e.g., RMSEA, CFI), comprehensively assessing the fit between the theoretical model and actual data, and systematically revealing the mechanisms through which each factor influences user satisfaction and behavioral intention.

2.5. Key Driver Analysis Model for Policy Support

To identify the most critical factors affecting public support for new energy policies, and to handle potential nonlinear relationships and interaction effects among variables, this study adopted the Random Forest model. Random Forest is an ensemble learning algorithm based on decision trees; it improves model accuracy and robustness by constructing multiple decision trees and aggregating their predictions. The core advantages of this model include its ability to handle high-dimensional data and a low risk of overfitting. More importantly, it provides a ranking of the "feature importance" of each input variable (independent variable) relative to the predicted target (dependent variable, i.e., policy support). In this study, independent variables included users' vehicle model choice, evaluation of charging facility construction speed, income level, market outlook expectations, and so on. Through model training, the contribution of each factor to policy support was quantitatively output, enabling precise identification of the core driving forces influencing public attitudes.

3. Results

3.1. Analysis of Basic Sample Characteristics

The 978 valid samples collected in this survey provide a foundational dataset for analyzing the user base of urban new energy vehicle (NEV) charging infrastructure in Urumqi—a key reference for optimizing charging network layout and matching facility supply to regional demand. In terms of gender distribution, female NEV users account for 52.25%, slightly exceeding male users (47.75%). This gender balance indicates broad acceptance of NEVs across demographics, which is critical for formulating inclusive charging facility planning that avoids skewed resource allocation toward a single gender group. Regarding age structure, the 26–35 age group dominates at 51.23%. As the primary demographic adopting NEVs, this younger cohort typically has higher travel frequency and stronger demand for efficient charging services—findings that directly guide the design of high-efficiency charging solutions (e.g., fast-charging pile deployment) in areas with concentrated young populations. From a regional perspective, the Xinshi District (21.27%), Shayibake District (19.43%), and High-tech Zone (16.05%) collectively account for over half of the samples. This concentration reflects significantly higher NEV penetration in core urban areas compared to outlying districts and counties, highlighting the urgency of prioritizing charging infrastructure densification in core zones while formulating phased expansion plans for suburban areas to bridge the supply-demand gap. In terms of income level, middle-income groups with monthly incomes of 3,000–8,000 yuan make up 75.26% of the sample. As the main consumer group of NEVs, their charging behavior (e.g., sensitivity to charging costs, preference for cost-effective services) provides data support for optimizing charging pricing strategies and configuring facility tiers (e.g., standard vs. premium charging services) to balance operational efficiency and user affordability. For occupational distribution, company employees (38.65%), government/public institution staff (18.92%), and freelancers (17.69%) are the primary user groups. Their typical travel patterns—such as commuting peak hours for employees and flexible travel schedules for freelancers—offer critical insights for time-series scheduling of charging facilities (e.g., adjusting power allocation during peak commuting periods) and optimizing the spatial overlap between charging stations and high-travel-demand areas (e.g., office clusters, business districts).These sample characteristics lay a data foundation for subsequent analyses of charging demand patterns and facility optimization directions, ensuring that subsequent research on charging network layout, service efficiency improvement, and scheduling strategy design is grounded in real user demand and regional practicality.

3.2. Analysis of Key Drivers for Charging Facility Satisfaction

This study employs a multiple linear regression model to conduct an in-depth analysis of the factors influencing user satisfaction. The overall fit of the model is good (adjusted $R^2 = 0.553$, $F(23,954) = 53.532$, $p < 0.001$), indicating that the selected independent variables can explain 55.3% of the variance in user satisfaction.

Table 1. Analysis of significant factors in linear regression

Variable	Non-standardized coefficient(B)	Standardization coefficient(Beta)	Significance(p)	Influence direction
Charging fee	0.177	0.183	0.000**	Positive
Charging speed	0.243	0.247	0.000**	Positive
The rationality of the distribution of charging piles	0.252	0.249	0.000**	Positive
Safety of charging facilities	0.201	0.199	0.000**	Positive

The "Significance (p)" column marked with "**" is a commonly used significance level indicator in statistical analysis. Combined with the quantitative analysis logic adopted in this study and the conventional norms of empirical research in social sciences, its meaning is: The regression coefficient of the corresponding variable has passed the significance test at the $p < 0.01$ level **, indicating that the influence of this variable on "user satisfaction" has extremely high statistical reliability, and the probability of random error is less than 1%.

As shown in Table 1, the analysis clearly reveals four core factors that have a highly significant positive impact on user satisfaction. Among these, "rationality of charging pile distribution" ($\beta = 0.249$, $p < 0.001$) ranks first, indicating that the user's top concern is how easily they can find charging facilities. This is closely followed by "charging speed" ($\beta = 0.247$, $p < 0.001$), reflecting that time efficiency is a key pain point in the user experience. Additionally, "charging facility safety" ($\beta = 0.199$, $p < 0.001$) and "charging cost" ($\beta = 0.183$, $p < 0.001$) also have a significant impact on satisfaction. These results provide important insight into the current stage of development of the charging market in Urumqi: in a context where infrastructure is not yet fully established, users place higher importance on "convenience in terms of space and time" (that is, accessibility and efficiency), even more so than on sensitivity to "economic costs." In comparison, factors such as charging wait time, users' monthly income, and brand differences among different operators have no significant direct effect on satisfaction. This may suggest that before core service experience needs are met, these factors are not yet the main issues users consider when evaluating service quality.

3.3. Cluster Analysis of New Energy Vehicle User Profiles

Using the K-prototype clustering algorithm, this study successfully divided new energy vehicle owners in Urumqi into three distinctly different groups: “High-frequency Charging Pragmatists,” “Price-sensitive Type,” and “Technology Early Adopters,” accounting for 26.06%, 42.43%, and 31.51% of the sample, respectively.

As illustrated in Figure. 1, the three user groups exhibit significant differences across multiple characteristic dimensions, which visually verifies the effectiveness of the clustering results. The radar chart comprehensively displays the performance of each group in key indicators such as charging frequency, cost sensitivity, technology acceptance, service quality requirements, and policy attitude, clearly reflecting the heterogeneous needs among different user segments.

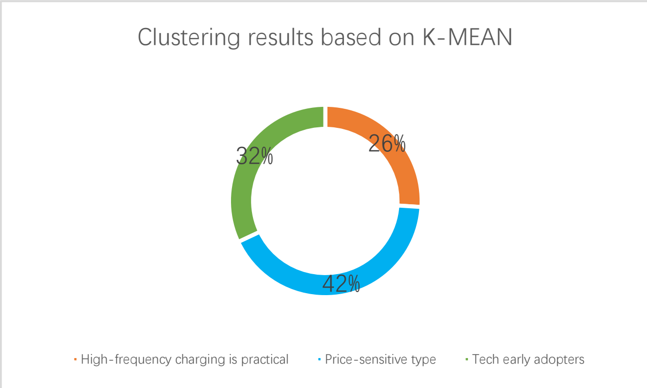

Figure 1. Radar Chart of Cluster Group Characteristics

The “High-frequency Charging Pragmatists” group mainly consists of company employees with mid-level incomes. Their core feature is a very high charging frequency, with high demands for the stability and speed of existing facilities, making them heavy users of the charging network. Their technological preferences are relatively conservative, placing greater emphasis on the reliability of basic services.

The “Price-sensitive Type” is the largest group in the sample, accounting for over 40%. This group has relatively lower incomes and is extremely sensitive to charging costs, with satisfaction scores being the lowest across all dimensions. They are also the least receptive to new technologies and represent the market segment most in need of cost advantages and preferential policies.

The "Technology Early Adopters" group comprises high-income and highly educated users, characterized by high charging frequency, strong acceptance of new technologies (e.g., smart reservations, integrated PV-storage-charging systems), and strict service quality requirements. This group serves as a core driver for technological upgrades and model innovation in the charging market, making them ideal early adopters for new charging products and services. The above segmentation results reflect notable heterogeneity in charging demand. A uniform operational strategy is infeasible; instead, differentiated measures should be developed to match the demand characteristics of different user groups, providing targeted support for optimizing charging facility layout and service configuration.

3.4. Analysis of the Impact Mechanism between Charging Facility Construction and User Behavior

The analysis results of the Structural Equation Model (SEM) reveal the complex causal transmission paths among various latent variables. The overall model fit is excellent ($\chi^2/df = 1.757$, RMSEA = 0.028, CFI = 0.996), indicating a high degree of consistency between the theoretical model and the actual data.

Table 2. Model fitting index

Model fitting index										
Common indicators	χ2	df	p	Chi-square ratio of degrees of freedomχ2/df	GFI	RMSEA	RMR	CFI	NFI	NNFI
Judgment criteria	-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
value	86.110	49	0.001	1.757	0.987	0.028	0.014	0.996	0.991	0.993
Other indicators	TLI	AGFI	IFI	PGFI	PNFI	PCFI	SRMR	RMSEA 90% CI	-	-
Other indicators	>0.9	>0.9	>0.9	>0.5	>0.5	>0.5	<0.1	-	-	-
value	0.993	0.973	0.996	0.461	0.534	0.536	0.013	0.018 ~ 0.037	-	-
Remarks：Default Model χ2(91) = 9786.599, p = 1.000										
AIC = 111.824, BIC = 385.412										

As shown in Table 2, the analysis found that “policy and environmental support” has a significant and extremely strong positive driving effect on the construction of “charging facilities” ($\beta = 1.042$, $p < 0.001$), confirming the core role of government guidance and macro policies during the popularization stage of infrastructure. At the same time, “technological foresight” significantly and positively influences users’ acceptance of innovative applications such as “smart reservations” and “integrated charging” ($\beta > 1.000$, $p < 0.001$), indicating that technological innovation is key to enhancing service value and user experience. A notable finding is that, although users’ perception of “basic services” (such as charging speed and convenient payment) is favorable in terms of hardware facilities, the path coefficient from the “charging service experience” (which includes soft services like customer service response) to “charging satisfaction” is not significant and even negative. This reveals a potential service shortcoming: while hardware facilities are being rapidly upgraded, they have not been fully matched by high-quality service management and user communication. The “soft power” of service quality has become a bottleneck restricting the overall improvement of user satisfaction.

3.5. Analysis of Influencing Factors for New Energy Policy Support

To explore the core factors influencing public support for policies, this study employed a random forest model. The model performed robustly on the test set ($R^2 = 0.440$, MAE = 0.618), demonstrating good predictive ability.

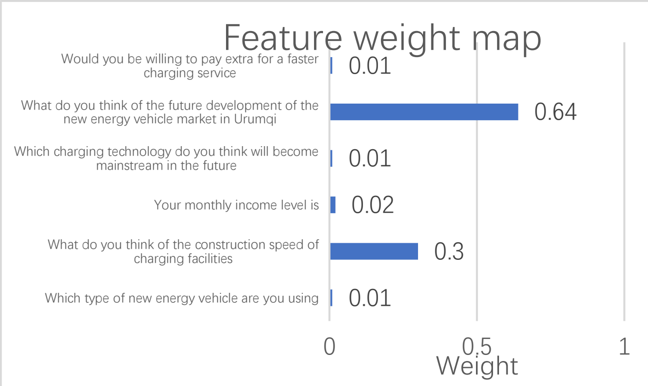

Figure 2. Feature Importance Chart

Table 3. Model evaluation results

Model evaluation results			
Indicator	Explanation	Training set time	Testing set time
R-squared value	The degree of fit index, the larger the range between 0 and 1, the better	0.549	0.440
Mean absolute error value (MAE)	L1 loss, the average difference between the true value and the fitted value, the closer it is to 0, the better	0.590	0.618
Mean square error (MSE)	L2 loss, the mean of the sum of squared errors, the closer it is to 0, the better	0.506	0.554
Mean square error root (RMSE)	MSE square root, average gap value	0.711	0.744
Median absolute error(MAD)	The absolute value of the residual of the predicted value from the median is not affected by outliers, and the smaller the better	0.485	0.502
Average absolute percentage error(MAPE)	The average percentage of error, unaffected by outliers, the smaller the better	1.843	0.487
Interpretable square difference (EVS)	Measure the model's explanatory power for data fluctuations within the range of [0,1], with the larger the better	0.549	0.455
Root mean square logarithmic error (MSLE)	When the RMSE is the same, it imposes more (less) penalties for underprediction.	0.036	0.042

Table 3 (Model Evaluation Results) quantifies the model’s performance comprehensively. On the training set, $R^2 = 0.549$ (explaining 54.9% of variance), MAE = 0.590, MSE = 0.506, and RMSE = 0.711, showing high fitting accuracy. On the test set, $R^2 = 0.440$ (maintaining explanatory power), MAE = 0.618, MSE = 0.554, and RMSE = 0.744—errors only slightly higher than the training set, indicating strong generalization and no obvious overfitting. Indicators like MAD (0.502), MAPE (0.487), and EVS (0.455) on the test set further confirm the model’s stability and low relative error.

As shown in Figure 2, the model's feature importance analysis provides highly insightful findings. Among all influencing factors, "the public's expectations for the future development prospects of the new energy vehicle market in Urumqi" stands out as the most decisive factor for policy support, accounting for as much as 63.6% of the weight. The next most important is "the perceived speed of charging infrastructure development," with a weight of 30.3%. Together, these two factors contribute over 93% of the total influence. In contrast, factors such as an individual's economic situation (e.g., monthly income level), specific vehicle model choices, and judgments about future technologies have only a negligible impact. These results overturn the traditional perception that public support for policies is primarily driven by direct economic benefits. The analysis shows that for industries like new energy, which have long-term development prospects, public support is more grounded in collective confidence about the industry's future and a tangible sense of comprehensive infrastructure. This suggests that when governments promote related policies, in addition to providing subsidies, it is even more important to shape and reinforce positive public expectations for the entire industrial ecosystem through effective publicity and visible construction achievements.

4. Conclusions

This study systematically uncovers the complex mechanisms influencing user satisfaction, behavioral patterns, and policy support in Urumqi's new energy vehicle charging market through an integrated multi-model analysis. The core contributions of the research are as follows: First, it clarifies that at the current stage of development, “spatial accessibility” (reasonable distribution) and “time efficiency” (charging speed) of charging stations have become the main pain points for users, outweighing price concerns. Second, through user profiling analysis, the study identifies three major mainstream groups with distinctly different needs— the “pragmatists,” the “price-sensitive,” and the “tech enthusiasts”— providing a basis for differentiated market operations. Finally, the study innovatively finds that public support for new energy policies primarily stems from macro-level confidence in the market’s future, rather than micro-level personal economic considerations.

Based on these findings and limitations, future research directions may unfold along several lines. On the modeling algorithm front, methods for deeper integration of structural equation modeling and machine learning algorithms can be explored— for example, using nonlinear relationships identified through random forests to optimize SEM path settings, thus creating more accurate mixed-effects models. In terms of research content, Geographic Information System (GIS) data can be introduced to more precisely match users’ charging behaviors with the spatial distribution of charging stations, thereby dynamically optimizing network layout. Finally, agent-based policy simulation studies can be conducted, using the user group characteristics and behavioral rules identified herein as input parameters, to simulate the long-term impact of different subsidy policies or construction plans on the overall market ecosystem, ultimately providing more forward-looking and intelligent support for government decision-making.

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