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Energy-Consumption-Based Accessibility and User-Centered Spatial Optimization of EV Charging Infrastructure in Ningbo, China

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ABSTRACT

Objective: This study evaluates the spatial accessibility and user-centered optimization priorities of electric vehicle charging infrastructure in the central urban area of Ningbo, China, by integrating road-network distance, driving energy consumption, and urban functional POI data. **Methods:** EV charging station POIs and urban functional POIs were collected from Amap, while administrative boundaries and road network data were obtained from public geospatial datasets and OpenStreetMap/Geofabrik. Road-network accessibility analysis, energy consumption estimation, and a refined priority identification model were used to evaluate charging service performance and identify priority areas for optimization. **Results:** A total of 1,306 EV charging station POIs and 9,426 urban functional POIs were identified. The median road-network distance to the nearest charging station was 0.626 km, indicating basic charging service coverage. However, accessibility varied across districts and POI categories. Beilun showed the greatest accessibility burden and estimated energy-consumption cost, while tourism-park, hospital, and school POIs showed weaker charging accessibility. The refined priority model identified 2,349 high- or very-high-priority POIs for potential service optimization. **Conclusion:** Ningbo has developed a relatively extensive EV charging infrastructure network, but spatial mismatch remains between charging supply and urban functional demand. Charging infrastructure optimization should consider road-network accessibility, energy-consumption cost, and user-centered functional scenarios.

Introduction

The rapid electrification of road transport has reshaped the technical, spatial, and service requirements of contemporary urban mobility systems. Electric vehicles (EVs) are increasingly regarded as a mature and commercially viable pathway for reducing local emissions, improving energy efficiency, and supporting the transition toward low-carbon transportation. Compared with conventional internal combustion engine vehicles, EVs are particularly suitable for urban environments because they operate quietly, generate no tailpipe emissions during use, and are well adapted to frequent start–stop driving conditions (Bin Ahmad et al., 2022). However, the large-scale diffusion of EVs does not depend only on vehicle-side technological progress. It also relies on whether charging infrastructure can provide accessible, energy-efficient, and user-responsive services across different urban functional contexts.

Recent studies in automotive engineering have paid considerable attention to improving the internal efficiency of EV systems. For example, research on EV energy system optimization has emphasized the importance of minimizing total energy consumption by integrating driving energy consumption, thermal management demand, low-voltage unit energy use, and battery state variation into a unified optimization framework (Ren, 2025). Other studies have focused on the allocation of power parameters in EVs, showing that refined parameter classification and optimization can improve both dynamic performance and energy efficiency (Liu et al., 2025). In parallel, regenerative braking control and intelligent steering stability control have been explored as important approaches

for extending driving range, improving vehicle safety, and enhancing energy recovery under complex operating conditions (Li, 2024; Zuo, 2025). These studies demonstrate that EV performance is not determined by a single component, but by the interaction among powertrain configuration, energy management, control strategy, and real-world driving conditions.

Although vehicle-side optimization is essential, users experience EV performance through actual travel processes, especially when charging decisions are involved. Range anxiety, detour distance, access time, waiting uncertainty, and the perceived convenience of nearby services all influence whether users regard EV mobility as reliable. Charging efficiency is also not merely a technical characteristic of charging equipment. It is closely related to where charging stations are located, how easily users can reach them through the road network, and whether they are embedded in suitable functional scenarios such as residential areas, commercial centers, workplaces, hospitals, schools, transport hubs, and recreational destinations. Research on wireless charging has shown that charging systems must improve not only power transfer efficiency but also operational adaptability and practical applicability (Wang and Li, 2024). This implies that the planning of charging infrastructure should be understood as a coupled engineering and service-system problem rather than only as a facility-location issue.

Existing studies on EV charging infrastructure have generally examined charging station siting, demand forecasting, grid interaction, or station utilization. These studies have provided useful planning models, but several limitations remain. First, many accessibility assessments still rely on Euclidean distance or administrative density indicators, which may underestimate the actual travel burden experienced by EV users. In real urban settings, access to charging facilities is constrained by the configuration of the road network, rivers, expressways, dead-end roads, land-use fragmentation, and parking entrance conditions. Second, charging demand is often represented by aggregate population or vehicle ownership data, while the differentiated demand generated by urban functions is less fully represented. Third, the link between driving energy consumption and charging infrastructure accessibility is still insufficiently integrated. For EV users, a charging station that is spatially close in straight-line terms may still impose high energy cost if the actual driving path is long or indirect. This gap is particularly important for infrastructure optimization because the objective is not only to increase the number of charging facilities, but also to reduce user-side access cost and improve service reliability.

To address these limitations, this study develops an energy-consumption-based accessibility framework for evaluating and optimizing EV charging infrastructure in the central urban area of Ningbo, China. The study integrates EV charging station points of interest (POIs), urban functional POIs, administrative boundaries, and OpenStreetMap road network data. It first identifies the spatial distribution of existing charging infrastructure and potential demand patterns derived from urban functional POIs. It then constructs a road-network-based accessibility model to estimate the travel distance from urban functional POIs to the nearest charging station. Based on this distance, the study further estimates energy consumption under multiple EV energy-use scenarios. Finally, a refined priority identification method is used to locate areas where charging infrastructure optimization is most needed.

This study contributes to the literature in three ways. First, it shifts the evaluation of EV charging infrastructure from simple facility density to road-network-based accessibility, thereby better reflecting the actual travel process of users. Second, it introduces urban functional POI data into charging demand identification, allowing the analysis to distinguish among residential, commercial, office, medical, educational, transport-parking, and tourism-park scenarios. Third, it connects accessibility analysis with driving energy consumption estimation and user-centered optimization strategies. By doing so, the study provides an integrated framework that links automotive energy efficiency, urban spatial structure, and user experience. The findings can support more refined charging infrastructure planning and contribute to the development of sustainable, energy-efficient, and user-oriented EV mobility systems.

The selection of Ningbo also has broader methodological and practical significance. As a coastal port city with a strong manufacturing base and diverse urban spatial structure, Ningbo differs from megacities such as Shanghai and Shenzhen, where EV infrastructure studies often focus on extremely high-density metropolitan conditions. Its urban form combines a historic core, newly developed commercial and residential districts, industrial zones, port-related areas, and peripheral tourism and ecological spaces. This spatial heterogeneity provides an appropriate context for testing whether EV charging infrastructure can respond to differentiated user needs across multiple functional scenarios. In this sense, Ningbo is not only a local case, but also a representative medium-to-large coastal Chinese city through which the relationship between charging accessibility, energy-consumption cost, and user-centered infrastructure optimization can be examined.

Literature Review

EV charging infrastructure planning and location optimization

The planning of electric vehicle (EV) charging infrastructure has been widely examined as a strategic problem involving transportation demand, power-system capacity, facility-location efficiency, and user acceptance. Early studies often treated charging stations as location-allocation facilities and focused on minimizing infrastructure cost, maximizing demand coverage, or improving service availability. Frade et al. (2011), for example, examined the optimal location of charging stations in a densely populated urban neighborhood in Lisbon and showed that population and employment concentration could provide a useful basis for slow-charging station deployment. Sadeghi-Barzani et al. (2014) further formulated the fast-charging station placement and sizing problem as a mixed-integer nonlinear optimization model, jointly considering transportation accessibility and grid-side effects. These studies established the foundation for treating charging infrastructure as a spatial optimization problem rather than only as an equipment-deployment issue.

Subsequent studies introduced richer representations of EV travel behavior and charging demand. Nie and Ghamami (2013) proposed a corridor-centric approach for charging infrastructure planning, emphasizing the interaction between charging station investment, battery size, and intercity travel feasibility. Xi et al. (2013) developed a simulation-optimization model for public EV charging infrastructure and demonstrated that charger type and budget allocation can influence system-level utilization. Dong et al. (2014) used multiday GPS travel data to evaluate charging infrastructure deployment from an activity-based perspective, while Cavadas et al. (2015) considered driver tours when locating slow-charging stations in urban areas. These approaches indicate that EV charging demand is strongly related to daily activity chains and cannot be fully represented by static population indicators.

More recent planning studies have increasingly integrated road-network structure, user behavior, and charging service levels. He et al. (2015) examined the deployment of public charging stations on urban road networks by considering travel and recharging interactions, while Wang et al. (2013) distinguished multiple types of recharging stations in the planning process. Reviews by Deb et al. (2018) show that the field has moved from simple siting models toward multi-objective optimization, demand uncertainty, grid interaction, and data-driven decision-making. However, many planning models still emphasize where stations should be installed from the supply side, while the user-side cost of reaching a station through the actual road network remains less fully integrated. This limitation is important because a charging station that appears close in Euclidean terms may still require long detours, especially in cities with rivers, expressways, fragmented land use, or discontinuous road networks.

Road-network accessibility and EV energy-consumption modeling

Accessibility is a central concept for evaluating whether charging facilities can effectively serve EV users. In transportation studies, accessibility is not only a matter of physical proximity but also a function of network connectivity, travel impedance, service availability, and destination attractiveness. In the context of EV charging, accessibility is closely related to range anxiety, detour distance, and charging decision-making. A corridor or node with a low straight-line distance to a charging station may still have poor practical accessibility if the road-network path is indirect or if the charging station is difficult to reach. Therefore, road-network-based accessibility is more appropriate than Euclidean distance for evaluating actual EV charging service levels.

EV energy consumption further complicates accessibility evaluation. Unlike conventional vehicles, EV users are directly concerned with the electricity consumed before reaching a charging station. Vehicle-side studies have shown that EV energy use is influenced by vehicle powertrain parameters, speed profile, road type, temperature, driving behavior, auxiliary loads, and traffic conditions. Fiori et al. (2016) developed a power-based EV energy consumption model and validated it with real driving data, while De Cauwer et al. (2015) showed that travel distance, travel time, temperature, and kinematic parameters can be used to predict EV energy consumption. Genikomsakis and Mitrentsis (2017) proposed a computationally efficient simulation model for EV energy consumption in route-planning applications, and Wu et al. (2015) examined EV energy consumption measurement and estimation based on real-world operation data. These studies confirm that routing and access distance are not only spatial variables but also energy-cost variables.

Research published in *Frontiers in Mechanical Engineering* also highlights the importance of vehicle-side energy optimization and control. Ahmad et al. (2022) discussed EV modeling in relation to future technology

pathways and market penetration, emphasizing the role of battery, motor, and vehicle-system interactions. Wang and Li (2024) investigated optimal-efficiency-point control during EV charging stages, while Ren (2025) proposed a machine-learning-based EV energy system optimization method. Liu et al. (2025) examined power parameter allocation for EVs, and Zuo et al. (2025) focused on regenerative braking control for energy recovery. Li (2024) investigated stability steering control for four-wheel-drive EVs. Together, these studies show that EV performance is shaped by both vehicle-side energy efficiency and operating conditions. Nevertheless, the link between these vehicle-level energy concerns and urban-scale charging infrastructure accessibility remains underdeveloped. This study responds to that gap by estimating the energy cost required for urban functional POIs to reach the nearest charging station through the road network.

POI-based urban functional demand identification

Charging demand is not spatially uniform. It emerges from different urban functions, user activities, and parking durations. Residential areas may generate overnight slow-charging demand, commercial centers may produce short-to-medium-duration charging demand during shopping and leisure activities, office districts may generate daytime charging demand, and hospitals, schools, transport hubs, and tourism spaces may create long-stay or event-based charging needs. For this reason, point-of-interest (POI) data have become increasingly important for identifying fine-grained urban functions and potential charging demand.

POI data provide semantic information about urban places, including location, category, service type, and functional meaning. Yuan et al. (2012) used POIs and human mobility data to discover regions of different urban functions, demonstrating that POIs can reveal the relationship between urban activities and spatial structure. Zheng et al. (2014) further showed that urban functional zones can be inferred from latent activity trajectories and POI information. More recent studies have used POI data with machine learning, remote sensing, street-view imagery, or mobility data to classify urban functional zones and built-environment patterns. Luo et al. (2023), for example, proposed an urban functional zone classification method based on POI data and machine learning, while Jiao et al. (2025) combined land-use maps, POI data, and computer-vision features to examine public EV charging patterns in relation to the built environment. These studies support the idea that POI data can serve as a high-resolution proxy for urban functional demand.

In EV charging infrastructure research, POIs are increasingly used as indicators of destination demand, service attractiveness, and site suitability. A systematic review of EV charging station locations by Katontoka et al. (2025) found that many studies use POIs and geographic attributes to support charging station allocation. Zheng et al. (2024) also showed that EV charging stations may influence customer visits and spending at surrounding POIs, implying a two-way relationship between charging infrastructure and urban service activities. However, existing POI-based studies often focus on site selection or utilization prediction, while fewer studies combine POI-derived demand with road-network accessibility and energy-consumption cost. This creates an opportunity to move beyond POI density mapping and toward a more operational framework in which urban functional demand, network travel cost, and EV energy use are evaluated together.

User-centered charging service design and spatial optimization

The success of EV charging infrastructure depends not only on technical capacity or spatial coverage, but also on whether users perceive the system as reliable, convenient, and easy to integrate into daily routines. Consumer-oriented studies have shown that charging infrastructure availability, charger reliability, access convenience, charging time, pricing, information clarity, and nearby amenities all affect EV adoption and charging behavior. Hardman et al. (2018) reviewed consumer preferences and interactions with EV charging infrastructure, noting that public charging availability and user confidence are closely related. Azadfar et al. (2015) examined factors affecting plug-in EV driving and charging behavior, while Andrenacci et al. (2023) reviewed private EV charging behavior and highlighted the role of charging anxiety, user experience, and infrastructure convenience. These studies suggest that charging infrastructure should be planned as a user-facing service system rather than merely as a physical engineering asset.

User-centered design also requires attention to the spatial and functional context of charging. Charging stations located near amenities, parking facilities, workplaces, hospitals, or commercial services may reduce perceived waiting cost because users can combine charging with other activities. Studies on accessible EV charging design also emphasize visibility, ease of use, safety, interface accessibility, and inclusive site design. From this perspective,

spatial optimization should not be limited to adding more charging stations. It should also identify where service pressure is high, where access distance or energy cost is excessive, and where information, guidance, waiting facilities, or functional integration should be improved.

Despite extensive research on EV charging station siting, energy modeling, POI-based urban analysis, and user behavior, there remains a methodological gap between these strands. Charging infrastructure planning studies often optimize facility locations but may not explicitly model user-side road-network energy cost. Energy-consumption studies often focus on vehicle-level performance but may not connect energy use with urban charging accessibility. POI-based studies reveal urban functional demand but may not evaluate whether those functions can efficiently access charging services. User-centered design studies identify experience factors but often lack spatially explicit analytical models. Therefore, this study integrates these perspectives by constructing a framework that links POI-based demand identification, road-network accessibility, EV energy-consumption estimation, and refined priority-area detection. This integrated approach allows EV charging infrastructure to be evaluated not only by where stations are located, but also by how users actually reach them, how much energy access requires, and which urban functional scenarios need targeted optimization.

Materials and Methods

Study area

This study focuses on the central urban area of Ningbo, Zhejiang Province, China. Ningbo is a coastal city in the Yangtze River Delta and has a mixed urban structure that includes historical urban districts, newly developed residential and commercial areas, industrial zones, port-related spaces, public-service facilities, and tourism and ecological destinations. This spatial heterogeneity makes Ningbo an appropriate case for examining the relationship between EV charging infrastructure, road-network accessibility, driving energy consumption, and user-centered service optimization.

The study area includes five core districts: Haishu, Jiangbei, Yinzhou, Zhenhai, and Beilun. These districts were selected because they represent the main built-up and functionally active areas of Ningbo, while also covering different spatial development patterns. Haishu and Jiangbei are closely related to the historical urban core and dense public-service functions; Yinzhou represents a rapidly developed commercial, residential, and administrative district; Zhenhai contains a mixture of residential, educational, and industrial functions; and Beilun is strongly associated with port logistics, industrial activities, and peripheral urban expansion. Therefore, the selected study area provides a suitable setting for evaluating whether the existing EV charging infrastructure can respond to differentiated urban functional demand.

Data sources and preprocessing

Four categories of spatial data were used in this study: EV charging station POIs, urban functional POIs, administrative boundary data, and road network data. EV charging station POIs and urban functional POIs were collected from the Amap Web Service API. Charging station POIs were obtained using charging-related keywords, such as EV charging station, charging pile, public charging station, State Grid charging station, TELD, and Star Charge. Urban functional POIs were collected using category-specific keywords related to residential, commercial, office, hospital, school, transport-parking, and tourism-park functions. After duplicate removal, category screening, and spatial cleaning, 1,306 EV charging POIs and 9,426 urban functional POIs were retained.

Administrative boundary data were used to define the central urban study area and support district-level statistics. Road network data were obtained from OpenStreetMap/Geofabrik and clipped according to the boundary of the study area. The clipped road network contained 33,451 road segments, with a total road length of approximately 14,600.53 km. Since the POI data collected from Amap were stored in the GCJ-02 coordinate system, while the road network data were stored in WGS84, all POI coordinates were converted to WGS84 before network analysis. This coordinate transformation was necessary to reduce spatial mismatch between POIs and the road network.

POI-based supply–demand characterization

A preliminary supply–demand analysis was conducted at the district level to compare the distribution of EV charging stations with the distribution of urban functional POIs. For each district, the number of EV charging POIs,

the share of charging facilities, the number of urban functional POIs, and the ratio of urban POIs to charging stations were calculated. The POI-to-charging-station ratio was used as a simple indicator of potential service pressure:

$$R_i = \frac{P_i}{C_i} \quad (1)$$

where R_i is the POI-to-charging-station ratio in district i , P_i is the number of urban functional POIs in district i , and C_i is the number of EV charging POIs in district i . A higher value of R_i indicates that more urban functional destinations are potentially served by each charging facility, suggesting relatively higher district-level service pressure.

This step was not intended to replace accessibility analysis, because district-level ratios cannot capture road-network constraints or intra-district spatial variation. Instead, it provided an initial overview of the spatial balance between charging supply and urban functional demand and supported the subsequent construction of a refined priority model.

Road-network construction and accessibility calculation

To measure the actual accessibility of charging facilities, a road-network-based model was constructed using the clipped OpenStreetMap road dataset. The road network was transformed into a graph structure ($G=(V,E)$), where (V) represents road network nodes and (E) represents road segments. Each edge was weighted by its geometric length. The resulting graph contained 220,183 nodes and 240,301 edges.

Both EV charging station POIs and urban functional POIs were snapped to their nearest road network nodes. This step allowed the calculation of travel distance along the road network rather than straight-line distance. For each urban functional POI, the shortest path distance to the nearest EV charging station was calculated using a multi-source shortest-path algorithm. All charging station nodes were treated as source nodes, and the shortest road-network distance from each urban functional POI node to the nearest source node was computed.

The road-network accessibility distance for each urban functional POI was defined as:

$$D_j = \min_{k \in C} d(n_j, n_k) \quad (2)$$

where D_j is the shortest road-network distance from urban functional POI j to the nearest charging station, C is the set of charging station nodes, n_j is the road network node associated with POI j , n_k is the road network node associated with charging station k , and $d(n_j, n_k)$ is the shortest path distance between the two nodes.

Compared with Euclidean distance, this method better reflects the actual travel burden of EV users because it considers road connectivity, network detours, and spatial barriers. The calculated road-network distance was further summarized by district and POI category.

Driving energy consumption estimation

To link charging accessibility with EV operating cost, the road-network distance was converted into estimated driving energy consumption. Since actual vehicle speed, traffic congestion, slope, vehicle type, temperature, and driver behavior were not available for all trips, this study adopted a scenario-based energy consumption estimation method. Three unit energy consumption scenarios were defined: low consumption, medium consumption, and high consumption. The corresponding values were 0.15, 0.18, and 0.21 kWh/km, respectively.

The estimated energy consumption from urban functional POI j to the nearest EV charging station was calculated as:

$$E_{\{j,s\}} = D_j \times e_s \quad (3)$$

where $E_{\{j,s\}}$ is the estimated energy consumption of POI j under scenario (s), D_j is the road-network distance from POI (j) to the nearest charging station, and e_s is the unit energy consumption rate under scenario s . The three scenarios provide a simplified but useful way to evaluate how accessibility distance may be translated into user-side energy cost under different EV operating conditions.

The medium scenario was used as the main reference for interpretation, while the low and high scenarios were retained to test the robustness of the energy-consumption pattern. This approach does not attempt to simulate detailed vehicle dynamics. Instead, it provides a spatially explicit approximation of the additional energy burden associated with reaching charging infrastructure.

Refined priority identification

A refined priority identification method was developed to locate urban functional POIs and areas where charging infrastructure optimization is most needed. The priority score combined three components: road-network distance percentile, district-level service pressure, and POI-category sensitivity. The road-network distance percentile represents the relative accessibility disadvantage of each POI. The district-level pressure reflects the preliminary supply–demand imbalance between charging facilities and urban functional POIs. The POI-category sensitivity reflects the importance of different functional scenarios from a user-centered service perspective.

The refined priority score was calculated as:

$$S_j = 0.70D_j^p + 0.20P_j^d + 0.10W_j^c \quad (4)$$

where S_j is the refined priority score of POI j , D_j^p is the percentile-normalized road-network distance of POI j , P_j^d is the normalized district-level service pressure of the district to which POI j belongs, and W_j^c is the category sensitivity weight of the POI category. The weights were set to emphasize accessibility distance as the dominant factor, while also incorporating district-level imbalance and user-centered functional differences.

Based on the refined priority score, POIs in the top 25% were classified as high-priority optimization points, while POIs in the top 10% were classified as very high-priority optimization points. This classification does not imply that all high-priority POIs require new charging stations. Rather, it identifies locations where charging infrastructure, access guidance, service integration, parking coordination, or user-oriented facility improvement should be considered first.

Outlier checking and visualization

To improve the reliability of the analysis, an outlier check was conducted after the accessibility calculation. POIs with road-network distances greater than the 95th percentile were treated as potential outliers or possible high-need locations. Additional attention was given to points with extremely high network distance, abnormal network-to-straight-line distance ratios, or large snapping distances to the nearest road node. These points may represent true accessibility gaps, peripheral destinations, disconnected road-network conditions, or possible geocoding and snapping issues. Therefore, they were reviewed before being interpreted as final planning recommendations.

The results were visualized using geographic information system tools and Python-based spatial analysis. The main outputs included the study area and road network map, the EV charging station distribution map, the road-network accessibility map, the energy consumption map, the refined priority area map, and boxplots comparing accessibility distances across districts and POI categories. For publication purposes, figures were exported in both PNG and TIFF formats at 300 dpi, with English labels and journal-style captions.

Results

Spatial distribution and preliminary supply–demand balance

A total of 1,306 EV charging station POIs and 9,426 urban functional POIs were identified in the central urban area of Ningbo. The study area and the clipped road network are shown in Figure 1. The road network is relatively dense in the central built-up districts, while peripheral and port-related areas show more dispersed road structures. This spatial pattern provides the basic network context for evaluating charging accessibility.



Figure 1. Study area and road network of the central urban area of Ningbo

Figure 2 presents the spatial distribution of EV charging stations. The charging facilities are not evenly distributed across the five districts. They are more concentrated in the central built-up areas and major urban functional clusters, while some peripheral, industrial, and port-related areas show relatively weaker coverage.

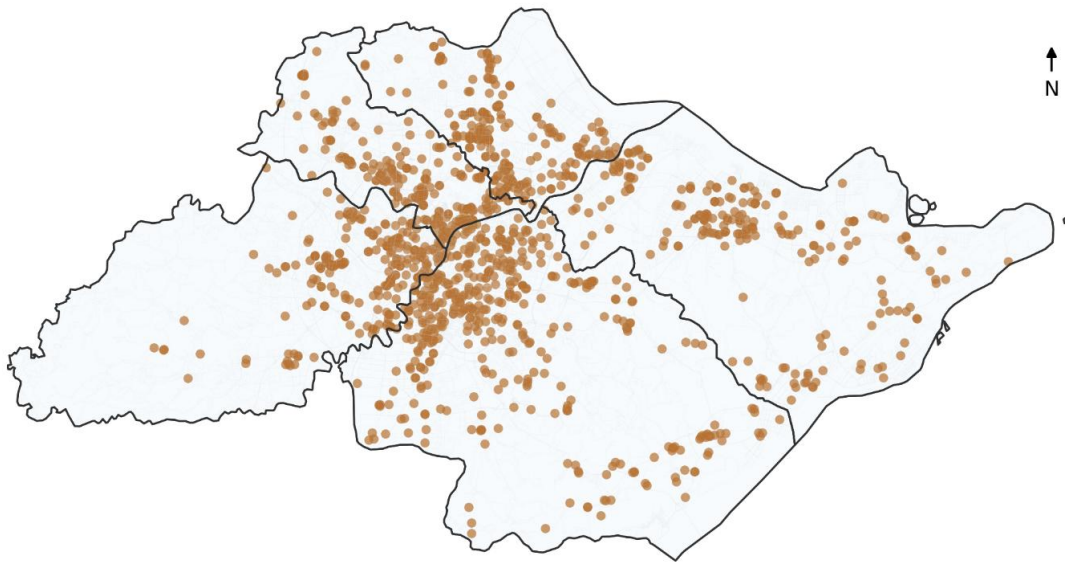


Figure 2. Spatial distribution of EV charging stations in the central urban area of Ningbo

Table 1 summarizes the preliminary supply–demand relationship between EV charging stations and urban functional POIs by district. Yinzhou had the largest number of EV charging POIs, with 433 stations, accounting for 33.15% of all identified charging facilities. However, its POI-to-charging-station ratio was the lowest, at 5.68, suggesting a relatively favorable balance between charging supply and urban functional demand. In contrast, Haishu and Beilun showed higher POI-to-charging-station ratios, at 9.00 and 8.09, respectively. This indicates that each charging station in these two districts potentially serves a larger number of urban functional destinations.

District	EV charging POIs	Charging share (%)	Urban functional POIs	POIs per charging station	Preliminary pressure level
Haishu	232	17.76	2,088	9.00	High
Jiangbei	220	16.85	1,566	7.12	Low
Yinzhou	433	33.15	2,458	5.68	Low

Zhenhai	207	15.85	1,583	7.65	Medium
Beilun	214	16.39	1,731	8.09	High

Table 1. Preliminary supply–demand relationship between EV charging stations and urban functional POIs by district.

These results indicate that the adequacy of EV charging infrastructure cannot be evaluated only by the absolute number of charging stations. A district with more charging facilities may still experience service pressure if it also contains a high concentration of urban functional destinations. Conversely, a district with fewer charging facilities may show lower pressure when demand-related POIs are also less dense. Therefore, the preliminary district-level comparison provides an initial indication of spatial mismatch, while road-network accessibility analysis is required to evaluate the actual user-side access burden.

Road-network accessibility to the nearest EV charging station

The road-network accessibility model was constructed using the clipped OpenStreetMap road dataset. The resulting graph contained 220,183 nodes and 240,301 edges. Urban functional POIs and EV charging stations were snapped to their nearest road-network nodes, and the shortest network distance from each urban functional POI to the nearest EV charging station was calculated. The overall median road-network distance was 0.626 km, while the 75th and 90th percentile thresholds were 0.993 km and 1.642 km, respectively. These values indicate that the charging infrastructure system in Ningbo’s central urban area has formed a basic level of service coverage, although local accessibility gaps remain.

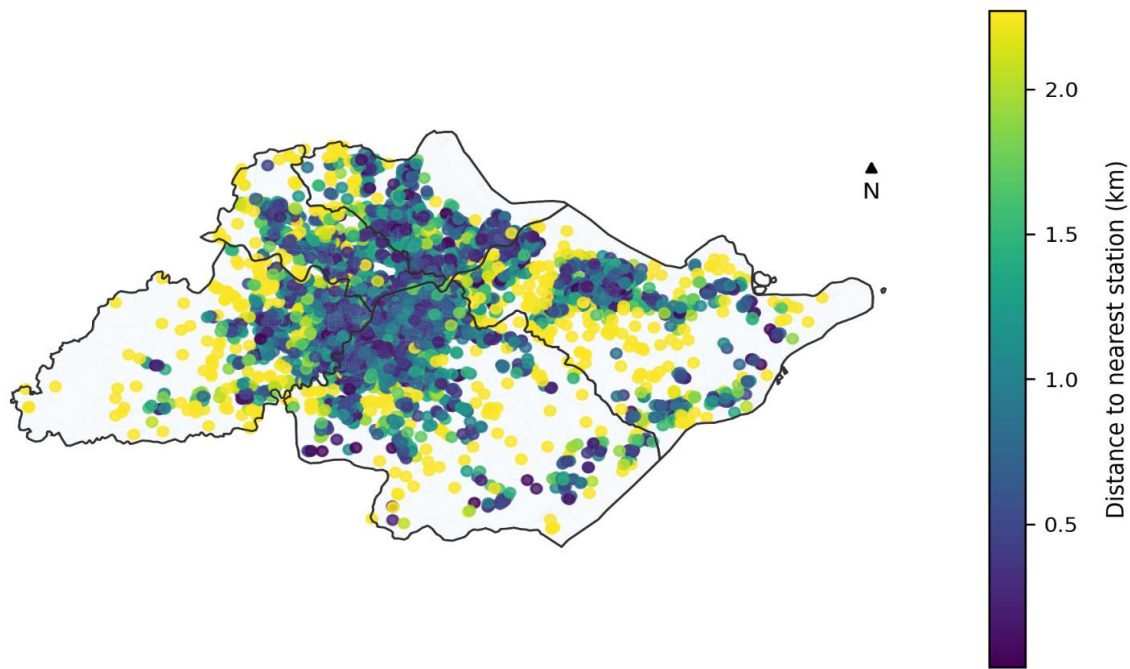


Figure 3. Road-network distance from urban functional POIs to the nearest EV charging station

Table 2 summarizes the district-level road-network accessibility and energy consumption statistics. Zhenhai had the shortest mean road-network distance, at 0.659 km, followed by Jiangbei at 0.736 km and Yinzhou at 0.796 km. Haishu had a higher mean distance of 0.921 km. Beilun showed the highest mean distance, reaching 1.124 km, indicating that urban functional POIs in Beilun generally experience a greater access burden when reaching the nearest EV charging station.

District	Urban functional POIs	Mean distance (km)	Median distance (km)	Max distance (km)	Mean energy, medium scenario (kWh)
Haishu	2,088	0.921	0.634	26.488	0.166
Jiangbei	1,566	0.736	0.568	7.409	0.133

Yinzhou	2,458	0.796	0.642	13.719	0.143
Zhenhai	1,583	0.659	0.506	4.793	0.119
Beilun	1,731	1.124	0.800	8.977	0.202

Table 2. District-level road-network accessibility and energy consumption statistics.

Figure 4 further compares the distribution of road-network accessibility distances across districts. The boxplot confirms that Beilun has a higher overall distribution of accessibility distance, while Zhenhai shows a more compact and lower-distance distribution. This result suggests that the spatial matching between charging facilities and urban functional destinations is relatively weaker in Beilun.

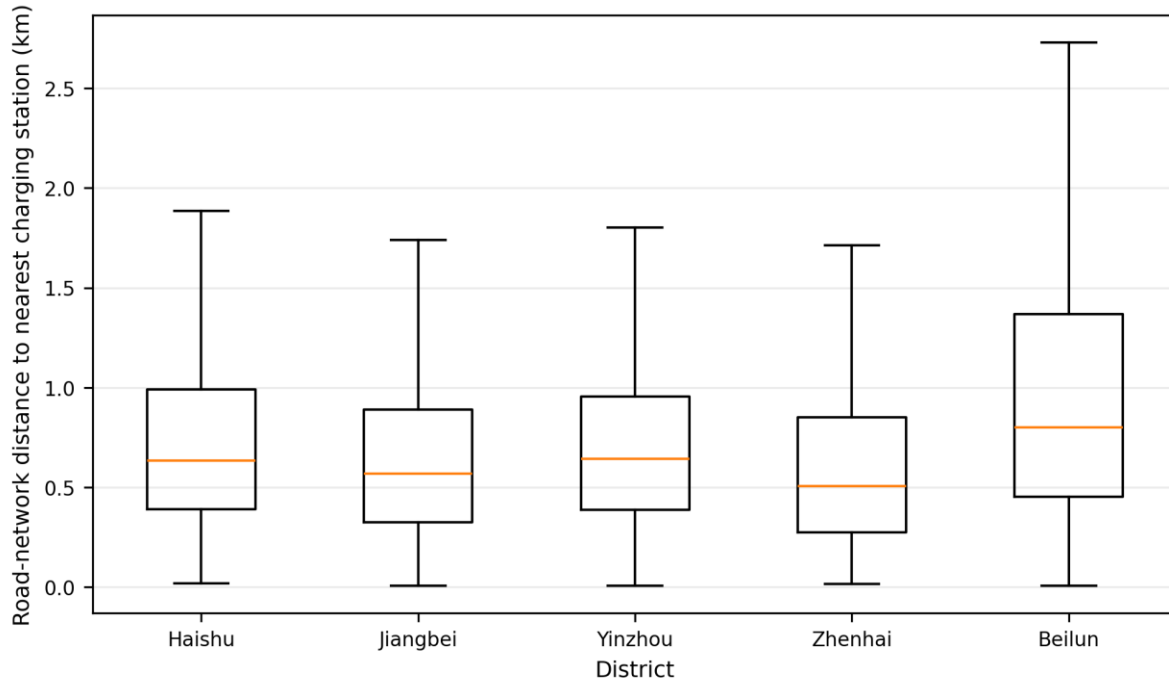


Figure 4. Distribution of road-network accessibility distance by district

The maximum distance values indicate the presence of local accessibility gaps or potential abnormal points. Haishu recorded the highest maximum value, at 26.488 km. Yinzhou and Beilun also contained POIs with relatively long access distances. These maximum values should not be interpreted as typical district-level conditions, but they suggest that some urban functional destinations may be affected by peripheral location, discontinuous road connectivity, network detours, or possible POI snapping issues.

Accessibility differences across urban functional POI categories

The accessibility results show clear differences across urban functional POI categories. Table 3 presents the road-network accessibility and energy consumption statistics by POI category. Commercial POIs had the lowest mean distance to the nearest charging station, at 0.589 km, suggesting that charging infrastructure is relatively well integrated with commercial service areas. Office POIs and transport-parking POIs also showed relatively favorable accessibility, with mean distances of 0.689 km and 0.698 km, respectively. Residential POIs had a mean distance of 0.716 km, indicating that residential charging accessibility is generally acceptable within the central urban area.

POI category	POI count	Mean distance (km)	Median distance (km)	Max distance (km)	Mean energy, medium scenario (kWh)
Commercial	836	0.589	0.494	3.435	0.106
Hospital	708	1.076	0.742	26.488	0.194
Office	1,428	0.689	0.526	6.260	0.124
Residential	2,558	0.716	0.636	5.815	0.129

School	1,176	0.854	0.713	23.352	0.154
Tourism/Park	1,445	1.425	0.881	25.361	0.256
Transport/Parking	1,275	0.698	0.512	7.147	0.126

Table 3. POI-category-level road-network accessibility and energy consumption statistics.

Figure 5 visualizes the distribution of accessibility distances by POI category. In contrast to commercial, office, and transport-parking POIs, hospital, school, and tourism and park POIs showed higher access distances. Hospital POIs had a mean distance of 1.076 km, while school POIs had a mean distance of 0.854 km. Tourism and park POIs had the highest mean distance, reaching 1.425 km, and also showed a wider distribution of accessibility distance.

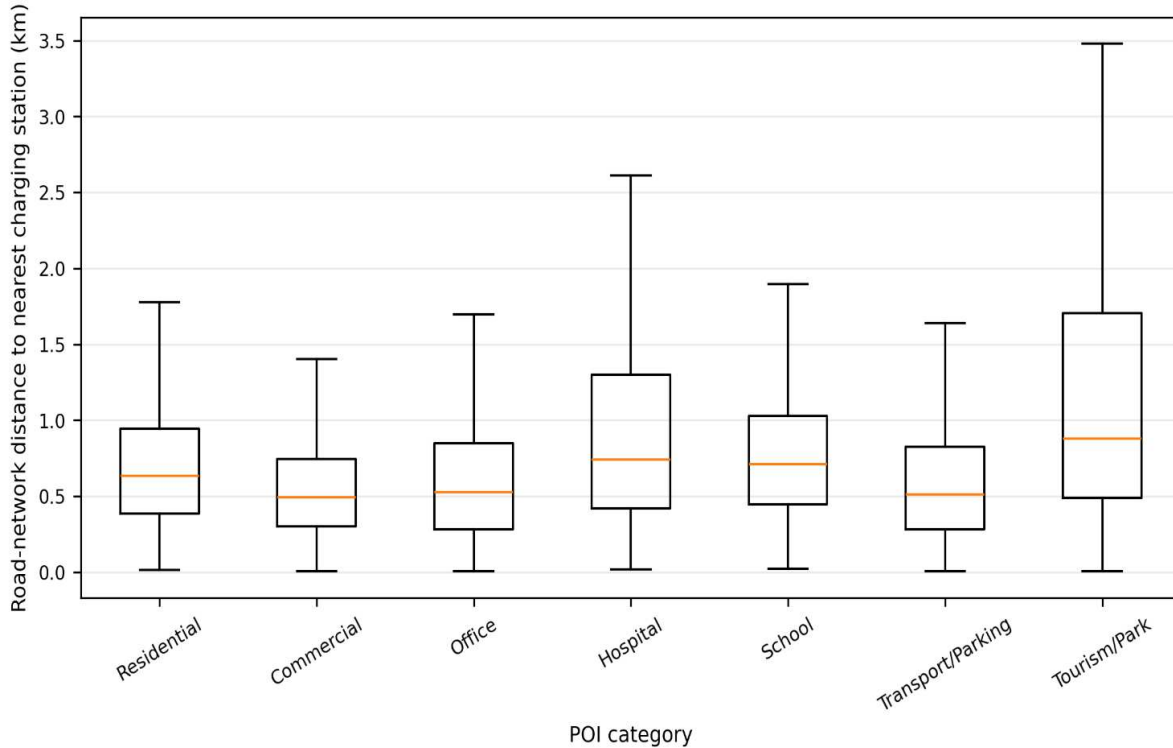


Figure 5. Distribution of road-network accessibility distance by POI category

The category-based comparison suggests that charging service accessibility is shaped not only by district-level infrastructure provision, but also by the functional attributes of urban destinations. Commercial and office destinations are often located in dense built-up areas where charging stations are more likely to be available. By contrast, tourism-park spaces, hospitals, and some school-related destinations may be located near waterfront areas, ecological spaces, large campuses, or less dense urban edges, where road-network access and charging infrastructure coverage are relatively weaker.

Energy-consumption-based accessibility pattern

To translate accessibility distance into an EV-specific operating-cost indicator, the shortest road-network distance from each urban functional POI to the nearest charging station was converted into estimated driving energy consumption. Three unit energy consumption scenarios were used: 0.15, 0.18, and 0.21 kWh/km. The medium scenario of 0.18 kWh/km was used as the main reference for interpretation.

The district-level energy consumption pattern is consistent with the accessibility results. As shown in Table 2, Beilun had the highest mean energy consumption under the medium scenario, at 0.202 kWh, followed by Haishu at 0.166 kWh and Yinzhou at 0.143 kWh. Jiangbei and Zhenhai showed lower mean values, at 0.133 kWh and 0.119 kWh, respectively. This confirms that the spatial burden of reaching charging infrastructure can be translated into additional user-side energy cost.

Figure 6 shows the spatial distribution of estimated energy consumption under the medium scenario. Its spatial pattern is generally consistent with the road-network accessibility map, because the energy-consumption estimate was derived from road-network distance. However, the energy map provides a more EV-specific interpretation by converting spatial separation into an operating-cost indicator.

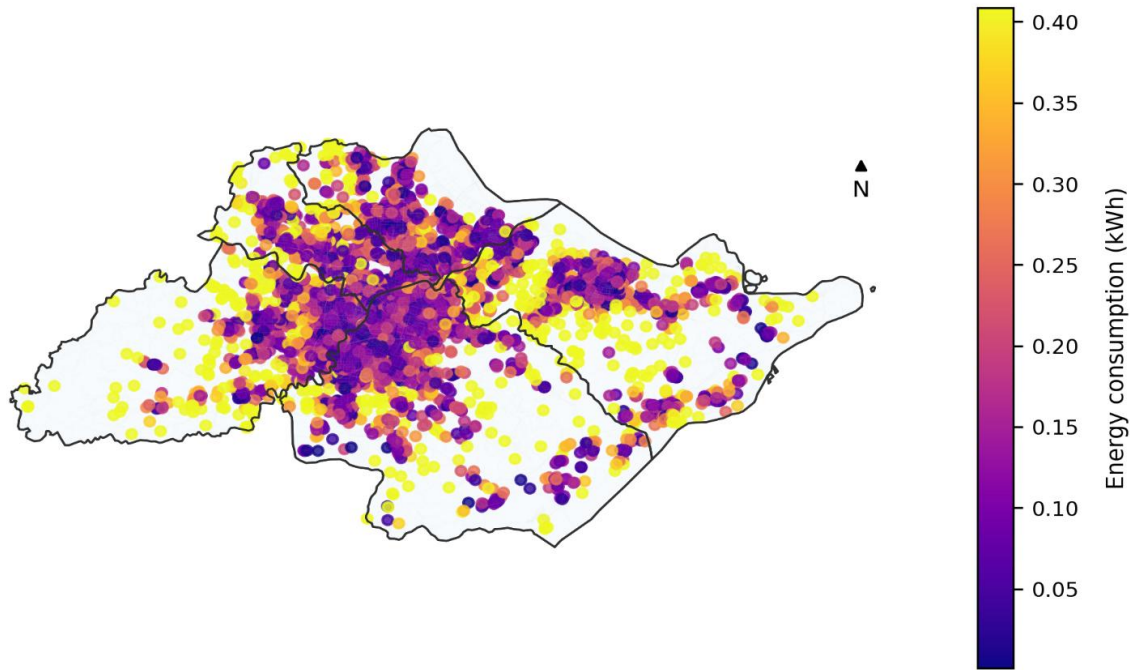


Figure 6. Estimated energy consumption from urban functional POIs to the nearest EV charging station under the medium scenario

The category-level energy pattern also follows the accessibility pattern. As shown in Table 3, tourism and park POIs had the highest mean energy consumption under the medium scenario, at 0.256 kWh, followed by hospital POIs at 0.194 kWh and school POIs at 0.154 kWh. Commercial POIs had the lowest mean energy consumption, at 0.106 kWh. Although these values may appear small at the single-trip level, they reflect repeated access costs that may accumulate through daily, weekly, or seasonal charging behaviors. More importantly, they provide an EV-specific interpretation of spatial accessibility by translating road-network distance into an estimated energy burden.

Refined priority areas for charging infrastructure optimization

The refined priority model combined road-network distance percentile, district-level service pressure, and POI-category sensitivity. Based on this model, 2,349 urban functional POIs were identified as high- or very-high-priority optimization points. POIs in the top 25% of refined scores were classified as high-priority points, while those in the top 10% were classified as very-high-priority points.

Table 4 presents the refined priority POI counts by district. Beilun showed the most prominent optimization need, with 363 high-priority POIs and 481 very-high-priority POIs, giving a total of 844 priority POIs. Haishu also showed considerable optimization pressure, with 354 high-priority and 257 very-high-priority POIs. Yinzhou had 380 high-priority and 148 very-high-priority POIs, suggesting that although its district-level supply–demand ratio was relatively favorable, local spatial mismatch still exists. Jiangbei had 176 high-priority and 54 very-high-priority POIs, while Zhenhai had 136 high-priority POIs and no very-high-priority POIs in the refined result.

District	Priority level	Priority POI count
Beilun	High	363
Beilun	Very High	481
Haishu	High	354
Haishu	Very High	257

Jiangbei	High	176
Jiangbei	Very High	54
Yinzhou	High	380
Yinzhou	Very High	148
Zhenhai	High	136

Table 4. Refined priority POI counts by district

Table 5 presents the refined priority POI counts by category. Tourism and park POIs formed the largest group of priority points, with 305 high-priority and 399 very-high-priority POIs. Residential POIs also contained a large number of high-priority points, with 396 high-priority and 90 very-high-priority POIs. School and hospital POIs showed notable optimization needs as well. Schools had 244 high-priority and 100 very-high-priority POIs, while hospitals had 134 high-priority and 148 very-high-priority POIs.

POI category	Priority level	Priority POI count
Commercial	High	69
Commercial	Very High	14
Hospital	High	134
Hospital	Very High	148
Office	High	157
Office	Very High	75
Residential	High	396
Residential	Very High	90
School	High	244
School	Very High	100
Tourism/Park	High	305
Tourism/Park	Very High	399
Transport/Parking	High	104
Transport/Parking	Very High	114

Table 5. Refined priority POI counts by POI category

Figure 7 shows the spatial distribution of refined priority areas. The identified priority points should not be interpreted as locations where new charging stations must necessarily be built. Instead, they represent areas where charging service improvement should be considered first. Potential interventions may include increasing charging facility density, improving parking–charging integration, enhancing route guidance and digital information services, coordinating charging with nearby public services, or upgrading existing charging facilities to better meet user needs.

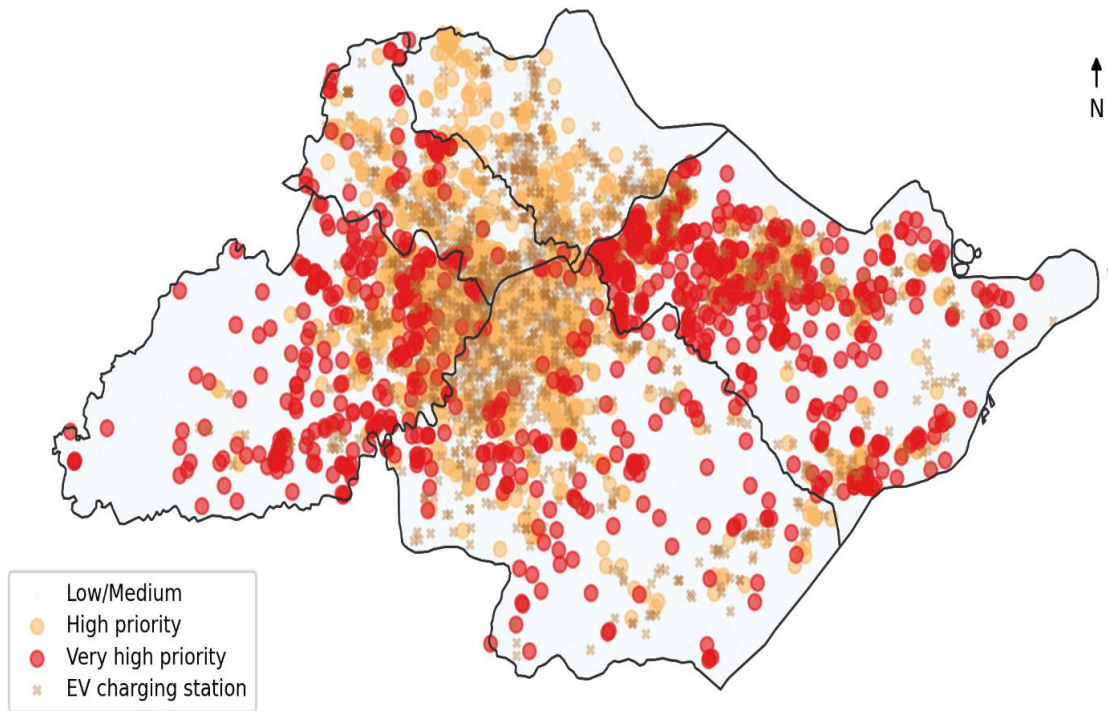


Figure 7. Refined priority areas for EV charging infrastructure optimization

Outlier check and reliability of results

An outlier check was conducted to avoid overinterpreting abnormal accessibility values. The 95th percentile threshold of road-network distance was 2.271 km, while the 99th percentile threshold was 4.644 km. A total of 608 POIs were identified as outliers or possible issue points. These points include POIs with extremely long road-network distances, potentially abnormal network-to-straight-line distance ratios, or possible snapping problems.

The presence of these outliers has two implications. On the one hand, some outliers may reflect real service gaps, especially in peripheral areas, large green spaces, port-related zones, or destinations with limited road-network connectivity. On the other hand, some may be associated with data quality issues, including geocoding error, incomplete road-network representation, or POIs being snapped to less appropriate road nodes. Therefore, the refined priority results were interpreted at the pattern level rather than as direct site-specific construction decisions.

Overall, the results indicate that Ningbo's central urban area has developed a relatively extensive EV charging infrastructure network, but accessibility and energy-consumption burdens remain uneven across districts and urban functional scenarios. Beilun and Haishu show higher optimization pressure at the district level, while tourism-park, hospital, and school POIs show higher accessibility burdens at the functional-category level. These findings provide an empirical basis for developing more user-centered and energy-consumption-aware EV charging infrastructure optimization strategies.

Discussion

From infrastructure quantity to network-based service quality

The results show that the evaluation of EV charging infrastructure should move beyond a simple count of charging stations and toward a more user-oriented understanding of service quality. In the central urban area of Ningbo, 1,306 EV charging station POIs have already formed a relatively extensive charging network. However, the district-level comparison and road-network accessibility analysis indicate that charging infrastructure provision is still spatially uneven. Yinzhou had the largest number of charging stations and the lowest POI-to-charging-station ratio, suggesting relatively favorable supply–demand balance. By contrast, Haishu and Beilun showed higher

preliminary service pressure, even though their absolute numbers of charging stations were not extremely low. This indicates that the adequacy of charging infrastructure depends not only on the number of facilities, but also on where they are located in relation to urban functional destinations.

This finding is consistent with the broader literature on EV charging infrastructure planning, which argues that charging station deployment should account for travel demand, user behavior, land-use structure, and road-network conditions rather than only facility density (Frade et al., 2011; Dong et al., 2014; Deb et al., 2018). In real urban mobility systems, users do not experience charging infrastructure through administrative counts. They experience it through access distance, detour burden, route convenience, parking availability, and perceived reliability. Therefore, road-network accessibility provides a more realistic indicator of user-side service quality than district-level supply statistics or Euclidean distance.

The Ningbo case demonstrates this point clearly. Although the overall median distance from urban functional POIs to the nearest charging station was only 0.626 km, the mean distance varied considerably across districts and POI categories. This suggests that the city has achieved a basic level of charging service coverage, but coverage does not automatically imply equal accessibility. Local mismatches may remain in areas where road networks are discontinuous, urban functions are dispersed, or charging stations are not well embedded in actual user activity spaces.

Spatial heterogeneity across districts

The district-level results reveal a clear spatial hierarchy in charging accessibility. Zhenhai showed the lowest mean road-network distance, followed by Jiangbei and Yinzhou, while Beilun had the highest mean distance and the highest refined priority score. This pattern reflects not only the distribution of charging stations, but also the spatial structure of each district. Zhenhai and Jiangbei have relatively compact urban structures in the selected study area, which may help reduce the network distance between functional destinations and charging stations. Yinzhou, although large and functionally diverse, has a relatively strong charging supply base, which may explain its favorable POI-to-charging-station ratio.

Beilun presents a different situation. As a port-oriented and industrial district, Beilun contains logistics, manufacturing, port-related land use, peripheral residential areas, and dispersed functional spaces. Such spatial characteristics can increase road-network travel distance even when charging stations exist within the district. The high number of very-high-priority POIs in Beilun suggests that charging infrastructure optimization should not be limited to central commercial areas. Instead, port-related, industrial, and peripheral functional spaces should also be incorporated into EV charging service planning.

Haishu also deserves attention. Although it is part of the historical and service-oriented urban core, it showed a high POI-to-charging-station ratio and a relatively high mean accessibility distance. This may be related to the dense concentration of urban functions, complicated road structure, older built environment, and limited parking space in central districts. In such areas, the key challenge may not be simply to add more charging stations, but to improve the integration of charging facilities with existing parking resources, public-service spaces, commercial complexes, and navigation systems.

These district-level differences suggest that EV charging infrastructure optimization should be spatially differentiated. For Beilun, the priority should be to strengthen charging coverage in port-related, industrial, and peripheral activity areas. For Haishu, the focus should be on improving the efficiency and usability of existing facilities within dense built-up environments. For Yinzhou, the main task may be to identify local mismatch points despite its overall favorable supply level. For Zhenhai and Jiangbei, maintenance of current service balance and targeted improvement of weak nodes may be more appropriate than large-scale expansion.

Functional scenario differences and user-centered charging service design

The POI-category results show that charging accessibility varies strongly across different urban functional scenarios. Commercial, office, and transport-parking POIs had relatively short access distances, while tourism-park, hospital, and school POIs showed higher accessibility burdens. This indicates that charging infrastructure is more closely integrated with dense urban service areas, but less closely integrated with public-service, recreational, ecological, and some institutional spaces.

This finding has important user-centered design implications. Charging behavior is not an isolated technical action. It is usually embedded in other activities, such as shopping, working, visiting hospitals, attending school,

commuting, or recreation. When charging stations are located near places where users already need to stay, the perceived cost of charging can be reduced. Users may combine charging with shopping, dining, working, medical visits, or leisure activities. By contrast, if charging requires an additional detour away from the user's activity space, even a short distance may be perceived as inconvenient.

Tourism and park POIs had the highest mean accessibility distance and the largest number of very-high-priority points. This suggests that recreational and tourism-related charging demand has not been fully integrated into the existing charging network. Such spaces often have seasonal or weekend peaks, longer parking durations, and users who may be less familiar with local charging resources. Therefore, charging service design for tourism and park destinations should not only focus on facility quantity, but also on wayfinding, parking coordination, real-time availability information, and integration with visitor services.

Hospitals and schools also showed relatively high accessibility burdens. These locations are sensitive from a service-equity perspective because they often involve time-constrained, vulnerable, or long-stay users. For hospitals, charging services may need to support patients, visitors, medical staff, taxis, and service vehicles. For schools and campuses, demand may come from staff, parents, visitors, and shared mobility users. In these scenarios, user-centered charging optimization should consider safety, walking distance after parking, visibility, accessibility for different user groups, and coordination with peak arrival and departure times.

Therefore, the priority areas identified in this study should not be interpreted only as locations for new charging station construction. They also indicate where service design intervention may be needed. Possible interventions include clearer digital guidance, improved signage, better parking–charging integration, differentiated slow and fast charging configurations, reservation functions, real-time occupancy information, and integration with nearby amenities. This interpretation aligns with consumer-oriented EV charging studies, which emphasize that charging confidence, convenience, reliability, and surrounding services are important determinants of EV user experience (Hardman et al., 2018; Andrenacci and Valentini, 2023).

Linking road-network accessibility with EV energy consumption

A further contribution of this study is that it translates road-network accessibility into estimated EV energy consumption. Many infrastructure studies evaluate charging accessibility using distance, coverage, or station density, while vehicle engineering studies focus on battery performance, powertrain efficiency, regenerative braking, or control strategies. However, EV users experience these two dimensions together. A poorly located charging station does not only increase travel distance; it also increases electricity consumption, detour burden, and potential range anxiety.

The energy-consumption results are consistent with the road-network accessibility pattern. Beilun had the highest mean energy consumption under the medium scenario, while tourism-park, hospital, and school POIs showed higher energy costs than commercial and office POIs. Although the estimated energy values are relatively small at the single-access level, their significance should not be underestimated. First, these values represent repeated access costs over many users and many charging events. Second, additional detours may influence charging choice, user confidence, and route planning. Third, energy-based accessibility provides a more EV-specific indicator than distance alone, because it connects urban infrastructure planning with vehicle operating efficiency.

This perspective is particularly relevant for engineering-oriented EV research. Vehicle-side studies have shown that EV energy consumption is affected by road type, speed profile, driving behavior, thermal load, and system efficiency (Fiori et al., 2016; De Cauwer et al., 2015; Ren, 2025). While this study adopts a simplified scenario-based energy estimation rather than a detailed vehicle dynamics model, it provides a spatial framework for linking charging infrastructure accessibility with user-side energy cost. Future research could further improve this framework by incorporating speed limits, congestion, slope, temperature, vehicle type, and real charging behavior data.

Implications for user-centered spatial optimization

The refined priority model provides a practical basis for identifying where charging services should be improved first. By combining road-network distance percentile, district-level pressure, and POI-category sensitivity, the model avoids relying on a single indicator. The results show that Beilun and Haishu require particular attention at the district level, while tourism-park, residential, school, hospital, and transport-parking POIs are important functional scenarios for optimization.

From a planning perspective, the findings suggest that charging infrastructure optimization should follow a differentiated strategy. In high-pressure peripheral or industrial districts, the priority may be to improve spatial coverage and reduce network detours. In dense central districts, the focus should be on facility integration, parking management, and service efficiency. In tourism and park areas, charging facilities should be coordinated with visitor flows, weekend demand, and wayfinding systems. In hospitals and schools, charging services should be designed around safety, accessibility, time sensitivity, and peak-period demand.

From a design perspective, the study supports a shift from facility-centered planning to user-centered charging service systems. A charging station should not be treated only as a physical device, but as part of an integrated mobility-service environment. The quality of this environment depends on spatial accessibility, parking convenience, digital information, waiting experience, surrounding services, and perceived reliability. Therefore, the priority points identified in this study can be used not only to guide station deployment, but also to support service-interface design, parking guidance, signage systems, platform-based information services, and scenario-specific charging facility upgrades.

Limitations and future research

Several limitations should be acknowledged. First, the EV charging POI data used in this study represent the spatial location of charging facilities, but they do not include detailed operational attributes such as charger number, charging power, pricing, opening hours, failure rate, or real-time occupancy. These factors may significantly influence actual charging service quality. Future research should integrate operational data from charging platforms if available.

Second, the urban functional POI dataset was used as a proxy for destination-based charging demand. Although POI data provide fine-grained spatial and semantic information, they cannot directly represent actual EV ownership, charging frequency, parking duration, or user preferences. Future studies could combine POI data with mobile phone signaling data, parking records, charging transaction data, or travel survey data to better estimate real charging demand.

Third, the energy consumption estimation in this study was scenario-based and simplified. It used fixed unit energy consumption rates to translate road-network distance into energy cost. This approach is useful for spatial comparison, but it does not fully capture traffic congestion, driving speed, road slope, temperature, vehicle type, auxiliary load, or driving behavior. Future work could develop a more detailed energy consumption model using road attributes, real-time traffic data, and vehicle-specific parameters.

Fourth, the outlier analysis showed that some POIs may be affected by geocoding uncertainty, network discontinuity, or snapping error. Although the study treated these points cautiously, more detailed local verification would be needed before translating individual priority points into site-specific construction decisions. Field investigation, high-resolution parking data, and local planning documents could improve the reliability of implementation-level recommendations.

Despite these limitations, this study provides an integrated framework for evaluating EV charging infrastructure from the perspective of road-network accessibility, energy-consumption cost, urban functional demand, and user-centered optimization. The framework can be transferred to other medium-to-large cities where EV adoption is growing and charging infrastructure needs to be evaluated not only by facility quantity, but also by service accessibility and user experience.

Conclusion

This study developed an energy-consumption-based accessibility framework for evaluating and optimizing EV charging infrastructure in the central urban area of Ningbo, China. By integrating EV charging station POIs, urban functional POIs, administrative boundaries, and OpenStreetMap road network data, the study moved beyond simple facility-density evaluation and examined charging services from the perspective of actual road-network accessibility and user-side energy cost. The results show that Ningbo has established a relatively extensive EV charging infrastructure network, with 1,306 charging station POIs serving 9,426 urban functional POIs. However, the spatial matching between charging supply and urban functional demand remains uneven. Haishu and Beilun showed higher preliminary service pressure, while Beilun had the highest mean road-network distance and energy-consumption burden. At the functional-category level, tourism-park, hospital, and school POIs showed weaker charging

accessibility than commercial, office, and transport-parking POIs. These findings indicate that EV charging infrastructure planning should not rely only on station quantity, but should also consider road-network conditions, urban functional scenarios, and user-side access costs.

The study further identified refined priority areas by combining road-network distance percentile, district-level pressure, and POI-category sensitivity. The results suggest that charging infrastructure optimization should be spatially differentiated and scenario-oriented. In port-related and peripheral districts such as Beilun, optimization should focus on improving spatial coverage and reducing network detours. In dense central districts such as Haishu, the priority should be the integration of charging facilities with existing parking resources, public services, and digital guidance systems. For tourism-park, hospital, school, and residential scenarios, user-centered charging service design should consider not only facility deployment, but also parking convenience, route guidance, waiting experience, safety, and functional integration with surrounding services. Although this study is limited by the absence of real-time charging operation data, detailed vehicle parameters, and individual charging behavior records, it provides a transferable analytical framework for linking EV energy consumption, urban spatial structure, and charging service optimization. Future research can further improve this framework by incorporating charging transaction data, traffic conditions, vehicle types, and real-time station availability.

Data availability statement

The POI data used in this study were obtained from Amap, and the road network data were obtained from OpenStreetMap/Geofabrik. The processed data and analysis results are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author contributions statement

WZ contributed to conceptualization, methodology, data collection, data processing, spatial analysis, visualization, and writing of the original draft. JW contributed to data organization, literature review, result interpretation, and manuscript revision. HL contributed to supervision, research design, methodological guidance, manuscript review, and overall project coordination. All authors contributed to the article and approved the submitted version.

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Supplementary Material

No supplementary material was submitted for this article.

Ethics Statement

Ethical review and approval were not required for this study because it did not involve human participants, human biological materials, personal identifiable information, or animal experiments. The study was based on publicly

accessible and third-party geospatial datasets, including POI data and road network data, which were analyzed only at the spatial and aggregate levels.

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