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# Towards a combined framework for public electric vehicle charger accessibility in London☆

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ABSTRACT

Over the past decade, the accessibility of electric vehicle (EV) infrastructure has been predominantly measured from a spatial proximity-based perspective, often overlooking the user's perspective. While calculated accessibility provides valuable insights, it does not necessarily translate into actual charging behaviour. Given the growing recognition that perceived accessibility plays a critical role in shaping user decisions, there is a clear need for tools that integrate both objective and subjective measures. To address this gap, this study proposes a combined accessibility framework that integrates calculated, perceived, and prospective accessibility to provide a holistic understanding of EV infrastructure accessibility. Using London as a case study, this research adopts a mixed-methods approach and introduces a typology of accessibility profiles. The study reveals two key findings. First, the relationship between calculated and subjective accessibility is nuanced and complex, with a spectrum of alignment identified across four clusters—ranging from moderate agreement to strong disagreement. Second, eight key features related to the built environment, demographics, and travel behaviour are identified as the primary drivers of these patterns. These findings reinforce the importance of incorporating multiple dimensions of accessibility into EV infrastructure planning. By acknowledging the gap between modelled accessibility and user experience, this approach offers a valuable tool for designing more user-centred and responsive EV charging networks.

## 1. Introduction

The UK government has set ambitious targets to achieve net-zero emissions, including a ban on the sale of new petrol and diesel cars by 2035. Expanding the public electric vehicle (EV) charging network is a critical element of this strategy (HM Government, 2022), particularly in urban areas such as London. However, despite these policy efforts, the uptake of EVs remains slower than anticipated, with the majority of car sales still dominated by conventional vehicles. This highlights the pressing need for more targeted approaches to encourage the transition to electric mobility and accelerate progress towards sustainable transport goals. High accessibility to EV charging infrastructure has been shown to significantly influence public intentions to adopt EVs (Coffman et al., 2017; Canepa et al., 2019), while also generating important environmental benefits (Liang et al., 2023). Therefore, understanding and improving accessibility to public EV charging infrastructure is critical not only for supporting the widespread adoption of EVs, but also for encouraging continued use and preventing users from switching back to conventional vehicles, ultimately helping to achieve the UK's decarbonisation targets.

While accessibility to EV charging infrastructure has been widely studied over the past decade—driven by the rapid growth of the EV industry and increasing rates of adoption—most existing research (Hsu and Fingerman, 2021; Falchetta and Noussan, 2021; Roy and Law, 2022) has focused on calculated accessibility. This typically involves spatial proximity-based measures such as charger density, distance, and travel time. Recent advancements have extended this work by incorporating temporal perspectives and spatial subdivisions by policy context. For instance, Park et al. (2022) examined the hourly variation of accessibility to public EV charging networks in Seoul, Korea, accounting for fluctuations in charging demand and supply. Similarly, Zhang et al. (2024) analysed differences in accessibility across London's traffic emission zones, highlighting the importance of spatial policy subdivisions.

However, existing studies on public EV charging accessibility have three key limitations. First, while research on calculated

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accessibility—typically based on objective measures such as distance, density, and travel time—has advanced significantly, perceived accessibility has received limited attention in this context. Perceived accessibility, defined as an individual's subjective sense of how easily they can reach their desired destination (Negm et al., 2025; Pot et al., 2021), plays a critical role in shaping charging behaviour (Pot et al., 2023; Negm et al., 2025). Yet, despite widespread recognition that calculated accessibility does not always reflect actual user behaviour, most studies continue to prioritise proximity-based metrics. Second, while some research has examined the mismatch between perceived and calculated accessibility, or the factors influencing perceived accessibility (e.g., Lättman et al., 2016), studies have yet to move beyond treating these dimensions in isolation. This limits our understanding of how different accessibility measures interact to shape charging decisions, and constrains the potential for more responsive, user-centred EV infrastructure planning. Third, prior research has tended to generalise the relationship between calculated and perceived accessibility, often using broad regression models (Thronicker and Klinger, 2019; Olsson et al., 2021) or structural equation modelling (Zhu et al., 2024; Chau et al., 2024). These approaches typically provide global-level insights but risk oversimplifying the nuanced and complex interactions between individual users, the built environment, and travel and charging behaviours. By broadly categorising accessibility as either aligned or mismatched, existing work may obscure the diversity of user experiences and limit its relevance for practical planning applications.

To address these limitations, this study develops a combined accessibility framework that integrates calculated, perceived, and prospective accessibility to provide a more comprehensive understanding of public EV charging infrastructure in London. This study makes two major contributions. First, it proposes a novel analytical framework that moves beyond proximity-based measures by incorporating subjective user perceptions and expectations into accessibility analysis. This integrated approach enables the capture of nuanced and complex interactions across different dimensions of accessibility, offering a more user-centred perspective on EV infrastructure. Second, the study applies clustering methods to segment users into distinct accessibility profiles and employs partial dependence analysis to further explore the relationships between socio-demographic, built environment, and behavioural factors and cluster membership. This combined approach identifies patterns of (mis) alignment between calculated and subjective accessibility across user groups, revealing where accessibility gaps exist and highlighting the key factors that contribute to these differences. These insights provide actionable evidence to inform more responsive and user-centred EV infrastructure planning and deployment strategies.

## 2. Literature review

### 2.1. Accessibility in public EV charging infrastructure

Research on EV charging infrastructure and services has expanded rapidly over the past decade, covering a diverse range of topics including charger placement and accessibility (Lam et al., 2014; Kłos and Sierpiński, 2023), charging demand and user behaviour (Wang et al., 2023; Jiang et al., 2024; Jonas and Macht, 2024), infrastructure resilience under uncertainty (Ahmad et al., 2023; Raman et al., 2022), and user experience studies (Fabianek and Madlener, 2023; Ha et al., 2021). Among these, accessibility studies have received particular attention, given the critical role that accessibility to public EV charging infrastructure plays in both sustainable transport planning and decarbonisation efforts. A well-connected and highly accessible charging network has been shown to significantly encourage the shift from conventional vehicles to electric vehicles, thereby accelerating EV adoption and supporting sustainable mobility goals. Furthermore, it is inherently linked to principles of inclusivity and transport equity, ensuring that individuals across different social, economic, and spatial cohorts have equitable opportunities to access charging services.

Hansen (1959) first brought the concept of accessibility to wider attention in his seminal work, defining it as "the potential of opportunities for interaction"—that is, the ease with which interactions can take place. This sparked the emergence of accessibility interpretations and measurement approaches. Numerous debates about the definition of accessibility (Handy and Niemeier, 1997; Geurs and Van Wee, 2004; Geurs et al., 2012) followed. Most developments and discussions around accessibility have focused on advancements in its measurement, such as proximity-based measures and buffer analysis (Roy and Law, 2022), the two-step floating catchment area method (Luo and Wang, 2003) and space-time measures (Weber, 2003).

In the context of EV infrastructure, accessibility can be understood as the ease of get access to charging services. On this conceptual basis, Zhang et al. (2024) summarise that existing accessibility studies on EV charging infrastructure and services can broadly be categorised into two types based on spatial scale: regional and neighbourhood-level studies, each employing different methods and focusing on distinct research interests. At the regional level, the primary focus is not on identifying specific areas but rather on understanding general spatial patterns and landscapes. Accordingly, measurement approaches tend to rely on relatively simple and computationally efficient indicators, such as the number of charging points per kilometre (Pemberton et al., 2021), charging point density (Falchetta and Noussan, 2021), or average travel time to the nearest charging station (Carlton and Sultana, 2024). Unsurprisingly, studies consistently reveal pronounced spatial disparities in accessibility. For example, significant gaps have been identified between Northern and Southern Europe, while in the United States, even starker disparities emerge between census tracts within and outside designated charging corridors. These findings raise important equity concerns, as they highlight potential misalignments between the distribution of charging infrastructure and governmental equity objectives.

Compared with the relatively limited number of regional-level studies, most research on EV charging accessibility has been conducted at the neighbourhood scale, particularly in China and the United States (e.g., Choi et al., 2025; Yu et al., 2025), with only a few exceptions such as studies from India (Jha et al., 2025).This focus is largely attributed to the rapid development of EV infrastructure in these countries and the availability of granular data. Similar to regional-level studies, some neighbourhood-level research has examined the spatial disparities in accessibility, seeking to identify whether spatial heterogeneity exists. For example, Li and his colleagues (Li et al., 2022) investigated ten Chinese cities and found that cities like Shanghai exhibited severe spatial inequities in charging infrastructure provision, highlighting the need for targeted interventions. Beyond spatial disparity, many neighbourhood-level studies have examined how specific population groups may face inequities in access to charging infrastructure. For instance, previous work has identified that low-income households (Roy and Law, 2022; Mehditabrizi et al., 2025), Black and Hispanic majority neighbourhoods (Hsu and Fingerman, 2021), populations with lower education levels (Malabanan et al., 2025; Peng et al., 2024), and specific family compositions (Roy and Law, 2022) are more likely to experience accessibility challenges compared to other groups. The recent EV Charger vertical equity studies such as.

Recent advancements in EV charging accessibility studies have focused on two key areas: embedding temporal perspectives and spatial subdivision by policy context. Recognising that accessibility is shaped by people, transport systems, and land use patterns, and that it varies over time (Geurs and Van Wee, 2004), recent research has begun to examine how accessibility to EV charging infrastructure and services interacts with temporal demand patterns. A few pioneering studies have attempted to measure space-time accessibility to EV charging stations, accounting for fluctuations in service availability and dynamic charging demand. However, the limited availability of temporal service data has constrained this line of research. Notable examples include Park et al. (2022), who identified five distinct temporal clusters of accessibility in Seoul, Korea, using hourly spatial accessibility measures over a 24-h period, and Zhou et al. (2021), who examined significant regional variations in accessibility across Nanjing, China, with peripheral suburbs showing the most pronounced fluctuations. In addition to incorporating temporal perspectives, some recent studies have sought to capture accessibility variations by subdividing urban space based on transport and energy policy regulations, acknowledging that policy context significantly shapes the distribution of charging infrastructure. For example, Zhang et al. (2024) examined neighbourhood-level accessibility in three different emission zones in London, revealing granular differences in accessibility and highlighting how vulnerable populations are differentially affected across regulatory contexts.

### 2.2. Beyond calculated accessibility

However, while research on EV charging accessibility has advanced considerably, it remains predominantly focused on proximity-based measures or referred to as calculated accessibility. This approach grounded in objective spatial analysis relies on methods such as 2-Step Floating Catchment Area analysis (Luo and Qi, 2009) relying on the distance to the nearest chargers, charger provision and speed, density etc. However, this perspective assumes that accessibility directly translates into behaviour, overlooking the subjective and cognitive processes through which individuals perceive and interact with their environment (Pot et al., 2021). As argues in theory of Cognitive behaviour theory (Golledge, 1997), spatial behaviour is shaped by both the objective properties of the environment and the individual's cognitive perceptions, attitudes, and knowledge of that environment. For instance, users may have limited awareness of public charging locations (Noel et al., 2020), experience range anxiety due to insufficient knowledge, or perceive financial constraints (Varghese et al., 2024). Such cognitive and perceptual barriers can hinder the actual adoption of EV charging, meaning that even individuals living in areas with high spatial accessibility may not make use of the available infrastructure. Therefore, calculated accessibility discussed above does not necessarily equate to actual charging behaviour, as it fails to capture how different individual interpret and process to their surroundings. As highlighted by Malabanan and his colleagues (Malabanan et al., 2025), both actual and perceived difficulties in accessing EV charging services can lead to charging disadvantages, thereby constraining individuals' full participation in social activities and discouraging EV adoption.

Perceived accessibility refers to an individual's subjective sense of how easily they can reach their desired destination using various modes of transport (Negm et al., 2025; Pot et al., 2021). The concept was first introduced by Morris et al. (1979), marking a departure from earlier approaches that focused solely on objective, spatial measures of accessibility. Compared to the substantial advancements in calculated accessibility, the development of perceived accessibility has been relatively limited, with much of the discourse remaining at the level of theoretical exploration. This is partly due to the challenges of quantifying subjective perceptions, as much of the available evidence remains anecdotal (Curl et al., 2011). The significance of distinguishing between calculated and perceived accessibility lies in the argument that while perceived accessibility may be derived from objective measures, it is ultimately perceived accessibility that serves as the true determinant of behaviour (Negm et al., 2025).

To the best of our knowledge, few studies have specifically examined perceived accessibility in the context of EV charging infrastructure, with two exceptions. These studies have explored how perceived accessibility influences non-EV owners' intentions to adopt EVs, as demonstrated in research from Hong Kong and China (He et al., 2022) and Montreal, Canada (Renaud-Blondeau et al., 2023). These findings suggest that for non-EV owners, low perceived accessibility to public charging infrastructure likely acts as a barrier to EV adoption. For current EV owners, although direct evidence is lacking, it is plausible that perceived accessibility influences a range of behaviours—including the choice of charging locations, which EV to use, charging frequency, and overall ease and satisfaction with the charging network. This assumption is supported by studies on conventional transport modes (e.g., buses and underground systems), where perceived accessibility has been shown to play a significant role in shaping broader transport planning objectives, including social inclusion (Lättman et al., 2016), ease of travel (De Vos et al., 2025), and sustainable travel behaviour (Negm and El-Geneidy, 2024).

Building on this distinction between calculated and perceived accessibility, recent work has proposed an additional dimension, namely prospective accessibility. He et al. (2022) extended the conventional dichotomy by introducing this concept to capture expectations about future accessibility. Drawing on Expectation Confirmation Theory (Oliver, 2014), which emphasises that adoption decisions are shaped by the alignment between prior expectations and subsequent experiences, prospective accessibility highlights how mobility choices such as EV adoption depend not only on current charging provision but also on anticipated developments in the charging network. In this sense, prospective accessibility reflects individuals' confidence that infrastructure will expand adequately to meet future needs. This consideration is particularly important for potential adopters who must make decisions under conditions of infrastructural uncertainty. As such, prospective accessibility should be regarded as an integral component of accessibility, especially during the current transitional phase from conventional vehicles to EVs, when both the pace and geography of charging infrastructure development remain uncertain.

In summary, while the literature provides valuable insights into the spatial and temporal dimensions of calculated accessibility for EV charging infrastructure, it remains fragmented. Existing studies tend to focus on isolated aspects of accessibility, overlooking how different dimensions interact to shape user behaviour and, ultimately, the effectiveness of EV charging networks. This creates a critical knowledge gap. Without integrating calculated, perceived, and prospective accessibility within a unified analytical framework, there is a risk of misrepresenting the realities of EV charging access and designing infrastructure that fails to meet diverse user needs. To address this gap, this study proposes a combined framework that brings together calculated, perceived, and prospective accessibility to build a more holistic understanding of EV charging accessibility.

## 3. Data and methods

Given the gaps in the existing literature where calculated accessibility does not necessarily translate into actual user behaviour—and the recognition that perceived accessibility plays a critical role in shaping charging behaviour, it becomes essential to broaden the scope of analysis. In response to this need, He et al. (2022), drawing on Expectation Confirmation Theory (ECT), introduced the concepts of perceived and prospective accessibility to capture how subjective perceptions and expectations influence EV adoption intentions. However, no study to date has combined calculated, perceived, and prospective accessibility into a unified framework that reflects both the objective conditions of the charging network and the subjective experiences and expectations that influence users' charging behaviour. This study proposed a combined accessibility framework that integrates calculated, perceived, and prospective accessibility, arguing that such a multi-dimensional approach is necessary to capture a more holistic and user-centred understanding of accessibility in the context of public EV charging infrastructure and services.

As shown in Fig. 1, three dimensions of accessibility are evaluated: calculated accessibility, perceived accessibility, and prospective accessibility. Calculated accessibility measures the possibility of engaging with various opportunities for interaction, typically using a proximity-based approach. Perceived accessibility refers to the perceived potential to participate in spatially dispersed opportunities. It is influenced by factors such as different transport modes, service quality, and individual characteristics—including age, income, and vehicle ownership (Negm

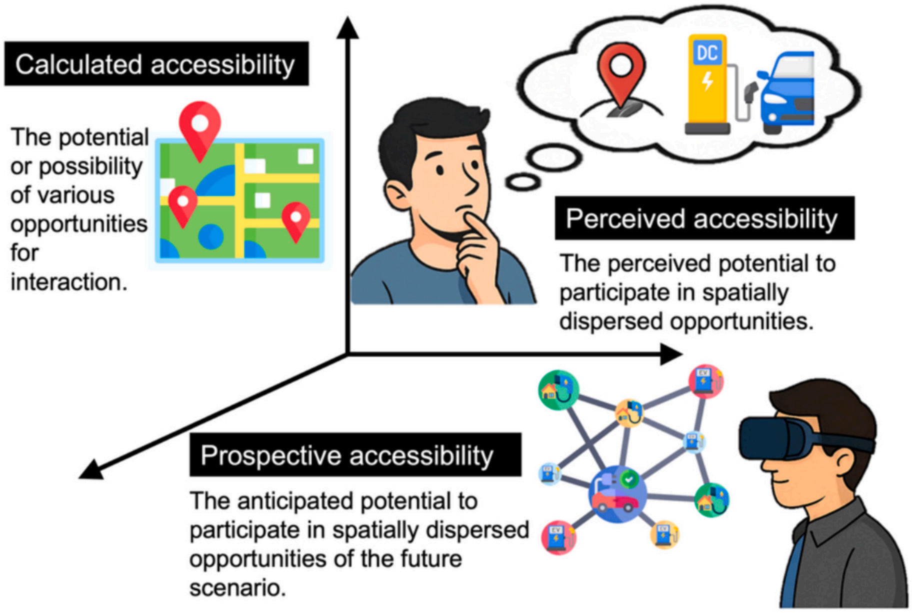


**Fig. 1.** A combined accessibility model for EV charging infrastructure and services.

et al., 2025). The final dimension, prospective accessibility, reflects the anticipated potential to participate in spatially dispersed opportunities in a future scenario. By combining them, accessibility to public EV chargers can be understood not merely as a spatial outcome, but as a cognitive and anticipatory process that influences behavioural choices and adoption trajectories. Translating this framework into empirical analysis, this study calculates three accessibility measures and employs the Min-Max Normalisation method to rescale them into a common value range. Specifically, following previous studies method (Zhang et al., 2024), calculated accessibility is derived using the Gaussian 2-Step Floating Catchment Area (2SFCA). The perceived accessibility and prospective accessibility measures are extracted through factor analysis applied to survey data. The detailed methods are elaborated below.

### 3.1. Data

We illustrate our method with a case study of the Greater London's public EV charging network. This study mainly uses two datasets. The first is the National Chargepoint Registry (NCR), published by the UK Department for Transport (D, which provides detailed information on public EV chargers, including their geographic location, charging speed, and other technical features. In this work, we group slow chargers (typically 3–7 kW AC) separately from fast and rapid chargers (above 7 kW AC, including ≥43 kW AC or ≥ 50 kW DC), following UK practice (Greater London Authority (GLA), 2019), as shown in Fig. 2a. The second dataset was derived from a primary survey conducted online in July 2024. Stratified sampling was used to achieve probability-proportionate representation by population size, ensuring the sample reflected Greater London's socio-demographic composition. This approach is particularly valuable for EV charging behaviour research, as charging needs,

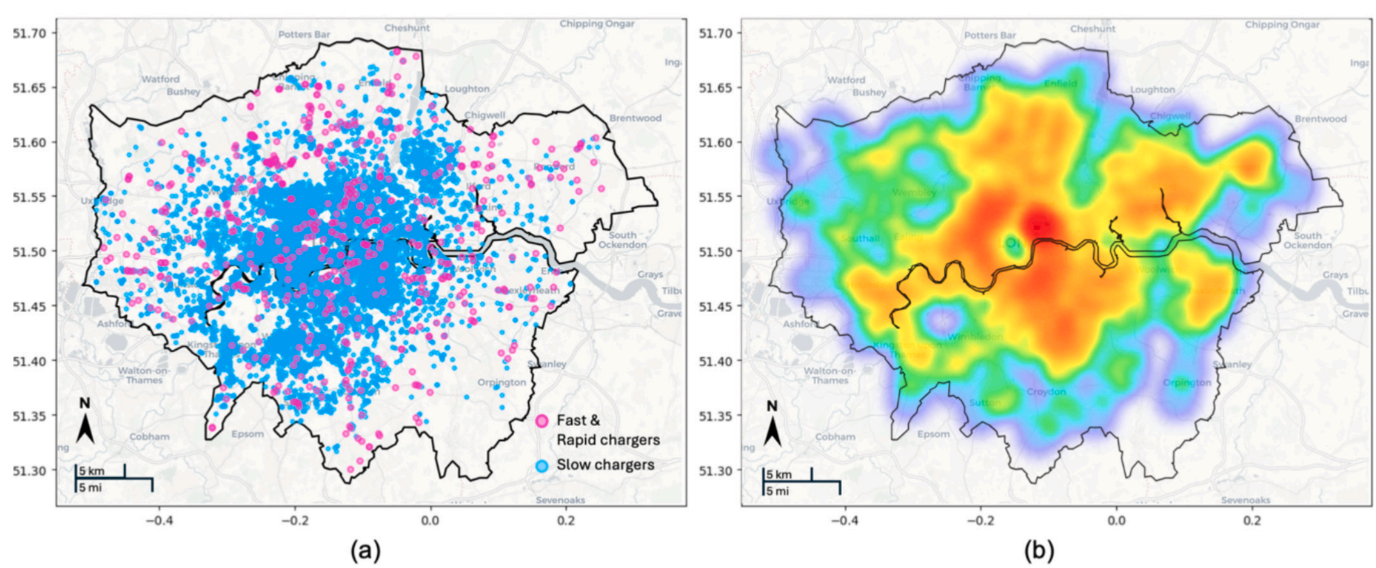


**Fig. 2.** (a) Spatial distribution of public EV chargers in London. (b) Geographical distribution of survey participants (heatmap used to indicate spatial density for confidentiality purposes, where red indicates areas with a higher number of participants and blue indicates areas with fewer participants.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

perceptions, and usage patterns can differ across demographic groups and locations. Eligible participants were aged 18 or over, resided within Greater London (verified via Prolific's location filter), and reported both EV driving experience and prior use of public EV chargers. The socio-demographic variables collected were informed by a review of relevant literature. The questionnaire comprised three sections: demographic variables, travel behaviour, and perceived and prospective accessibility. In total, 1088 valid responses were obtained, with participant characteristics summarised in Table 1.

### 3.2. Measuring calculated accessibility

To better capture calculated accessibility by accounting for both supply and demand factors, this study estimates calculated accessibility (also referred to as spatial accessibility) to public EV chargers using the Gaussian two-step floating catchment area (2SFCA) method.

In step one, the service area of charger location $j$ is defined as the area within 15 min walking zone ($d_0$ =1200 m; Park et al., 2022). Within each charger service area, the process involves searching all LSOA (neighbourhood) locations $k$ that are within a distance threshold $d_0$ from location $j$, and computes the charger's weighted capacity-to-population ratio, $R_j$ within the catchment areas as follows:

$$R_j = \frac{S_j f(S_j)}{\sum_{k \in \{d_{kj} \le d_0\}} D_k f(d_{kj})} \tag{1}$$

$$f(S_j) = \begin{cases} 4, & S_j \in AC \\ 48, & S_j \in DC \end{cases} \tag{2}$$

where $S_j$ is the type of EV chargers and $f(S_j)$ indicates the capacity of charger. Considering the varying charging capacity between Alternating Current (AC) and Direct Current (DC) chargers, this study assumes that a DC charger can serve 48 electric vehicles and an AC charger can serve four electric vehicles (Li et al., 2022). $D_k$ is the charging demand (indicated by the number of registered drivers at location $k$); $d_{kj}$ is the distance between EVCS location $j$ and demand location $k$.

The influence of supply and demand diminishes through each step as the distance increases, in accordance with the decay function $f(d_{kj})$, as mathematically represented in *Eq.* (3).

$$f(d_{kj}) = \begin{cases} \dfrac{e^{-\frac{1}{2}\left(\frac{d_{kj}}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}}, & \text{if } d_{kj} \le d_0 \\ 0, & \text{if } d_{kj} > d_0 \end{cases} \tag{3}$$

In step two, for each neighbourhood population location $k$, search all charger locations $j$ that are within the catchment areas of population location $i$, and aggregate the charger's capacity-to-population ratios (derived from step1), $R_j$, discounted by distance decay function $f(d_{kj})$.

$$A_k = \sum_{j \in \{d_{kj} \le d_0\}} R_j f(d_{kj}) \tag{4}$$

where $A_k$ is the accessibility values for neighbourhood location $k$. A lower $A_k$ value indicates limited accessibility for residents in that area, while a higher value indicates better EVCS accessibility.

### 3.3. Measuring perceived and prospective accessibility

In our London questionnaire survey, perceived and prospective accessibility were measured using a set of statements (see Table 2), which were developed based on previous work (He et al., 2022; Renaud-Blondeau et al., 2023). Respondents were asked to rate their level of agreement with these statements regarding the perceived and prospective accessibility of public EV chargers. Each item was rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). To assess the internal consistency of each construct, Cronbach's alpha was calculated. The results indicate good internal reliability, with a Cronbach's alpha of 0.88 for perceived accessibility and 0.79 for prospective accessibility, both exceeding the commonly accepted threshold of 0.70 (Nunnally, 1978). Given the satisfactory Cronbach's alpha values, the average score for each construct was calculated to represent perceived and prospective accessibility in the analysis. Therefore, a higher average score suggests a higher level of subjective accessibility.

### 3.4. Clustering segmentation and drivers

Using the postcode information provided by participants in the questionnaire, we first geocoded the addresses into geospatial

**Table 1**
Descriptive analysis of participants' characteristics.

| | Proportion/Mean (SD) |
|---|---|
| **Age (mean)** | 36.13 (11.13) |
| **Gender (%)** | |
| Male | 54.59 |
| Female | 44.30 |
| Others | 1.11 |
| **Education (%)** | |
| GCSE or equivalent | 7.40 |
| A-levels (high school) | 17.41 |
| Bachelor's degree | 49.45 |
| Master's degree and above | 25.74 |
| **Employment (%)** | |
| Full time | 78.67 |
| Part time | 11.76 |
| Student | 4.50 |
| Unemployed | 3.77 |
| Retired | 1.29 |
| **Income (%)** | |
| Less than £25,000 | 24.41 |
| £25,000- £34,999 | 24.81 |
| £35,000- £44,999 | 18.20 |
| Above £45,000 | 36.58 |
| **Daily travel distance (%)** | |
| <2.5 km | 17.10 |
| 2.5–5 km | 39.43 |
| 5–10 km | 29.87 |
| More than 10 km | 23.60 |
| **Daily travel duration (%)** | |
| ≤15 min | 13.79 |
| 15–30 min | 46.51 |
| 30–60 min | 34.83 |
| More than 60 min | 4.87 |
| **Charging frequency (%)** | |
| Never | 17.10 |
| Once a week | 53.95 |
| More than once a week | 28.95 |

**Table 2**
Measurement of perceived accessibility and prospective accessibility (developed based on He et al., 2022).

| | |
|---|---|
| Perceived accessibility | - There are enough public EV chargers available when I need them.<br>- Whenever I want to use the EV chargers I can find it.<br>- Public EV chargers are located near places I frequently visit, such as shopping centres, workplaces, and recreational areas.<br>- Public EV chargers are conveniently located for my daily travel needs. |
| Prospective accessibility | - I believe the number of EV charging stations will significantly increase in the next five years.<br>- I expect the locations of EV charging stations to become more convenient and accessible in the next five years.<br>- I believe the reliability of EV charging stations will improve, reducing the likelihood of encountering broken or non-functional chargers. |

coordinates. By performing a spatial join between the calculated accessibility values and participants' locations, we integrated the survey data with the calculated accessibility measures. In other words, for each individual in the dataset, we obtained a unique combination of calculated, perceived, and prospective accessibility values, along with their socio-demographic and travel behaviour information.

To ensure comparability among the three accessibility measures, we applied Min-Max normalisation to rescale each dimension to a common range from 0 to 1, where a higher value indicates greater accessibility. Following this, a K-means cluster analysis was conducted to identify distinct groups of respondents, minimising variance within clusters while maximising variance between them. The optimal number of clusters was determined using the average silhouette method (Rousseeuw, 1987). To capture the granular differences between clusters, we calculated the standard deviation (SD) across the means of the three accessibility measures (perceived, prospective, and calculated), as well as the range across the mean values. These indicators quantify the (dis)agreement between the three accessibility dimensions within each cluster. A standard deviation (SD) across the means below 0.1 and a range across means less than 0.2 indicate high agreement among the accessibility measures, whereas an SD exceeding 0.4 and a range greater than 0.5 suggest low agreement among the measures (Martinez and Bartholomew, 2017).

To investigate the key drivers of matches and mismatches among the three accessibility dimensions, as well as the differences between clusters, we modelled cluster membership (derived from the k-means clustering in the previous step) using four algorithms: Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), Random Forest, and Support Vector Machine (SVM). The hyperparameters for each model were tuned using a random search strategy, with the final configurations presented in the Appendix. Model performance was assessed through five-fold cross-validation, using both accuracy and F1-score to identify the best-performing model. The model incorporated socio-demographic, built environment, travel behaviour, and attitudinal factors (Lukina et al., 2021; van der Vlugt et al., 2019; Lättman et al., 2018), allowing for a nuanced understanding of how these variables shape accessibility outcomes.

To further understand how these features influence the model's predictions, Partial Dependence Plots (PDPs) were employed. The PDPs illustrate how varying a single feature while holding others constant affects the predicted probability of belonging to a specific cluster (Friedman, 2001). This approach provides a nuanced understanding of the relationships between individual features and cluster assignments, offering insights into the factors driving differences in accessibility profiles. By enabling a local-level interpretation of feature effects, the analysis helps identify cluster-specific enablers and barriers to accessibility, providing first-hand evidence to inform targeted policy interventions aimed at reducing accessibility differences.

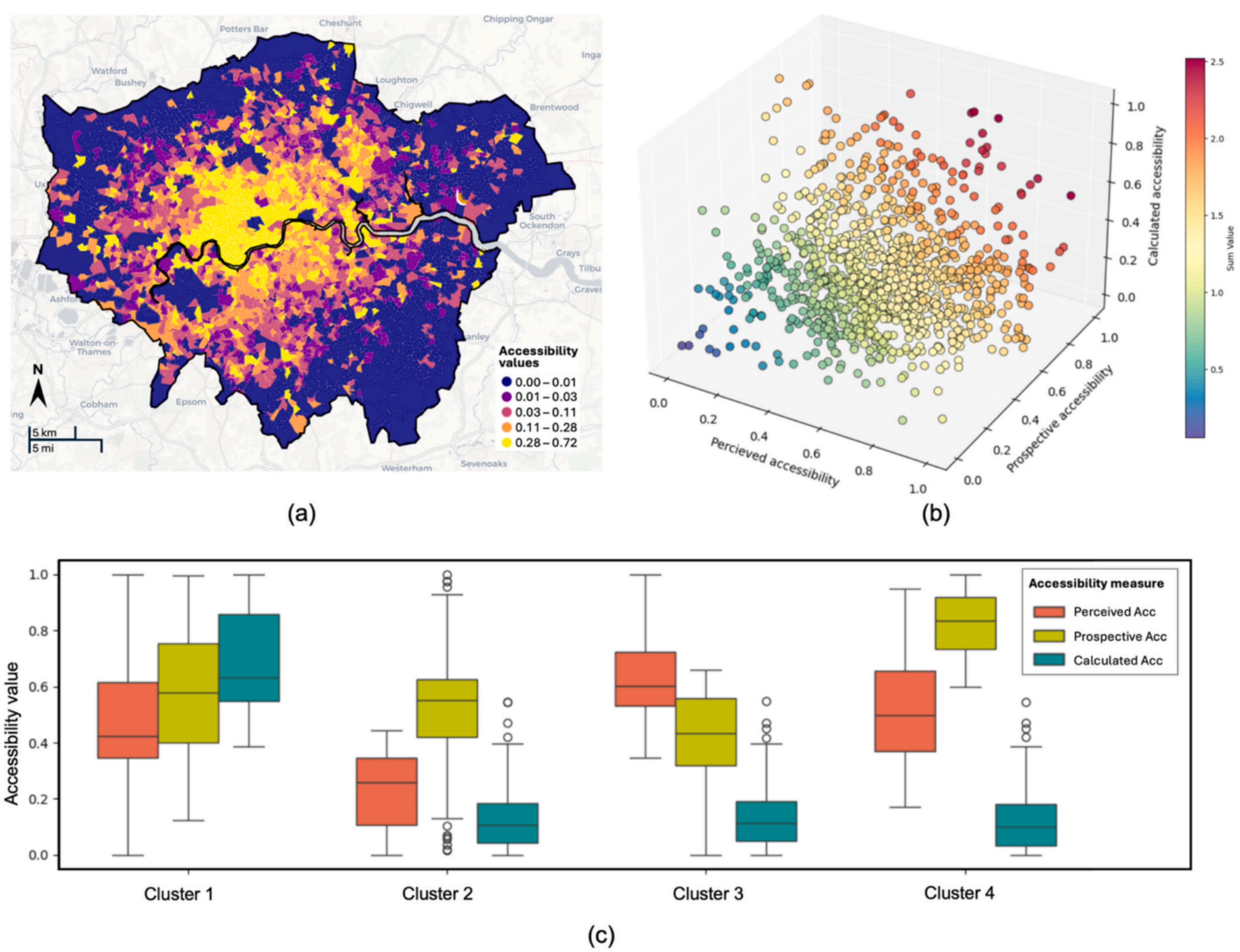


**Fig. 3.** (a) Spatial distribution of calculated accessibility to public EV chargers in London. (b) Scatter plot of calculated, perceived, and prospective accessibility values within the combined accessibility framework. (c). Box plots of the three accessibility dimensions by cluster.

## 4. Results and discussion

### 4.1. The combined accessibility

The calculated accessibility to public EV chargers in London, derived using the Gaussian 2-Step Floating Catchment Area (2SFCA) method at the neighbourhood level, is shown in Fig. 3a. The analysis reveals that the city centre, particularly areas in the north-central part of London, exhibits significantly higher accessibility compared to other regions. In contrast, suburban areas generally display lower accessibility; however, certain fragmented neighbourhoods within these areas stand out with higher accessibility levels. These include key suburban town centres and major transport hubs—such as Heathrow Airport—where, despite being located on the western periphery of London, accessibility is notably high due to the substantial provision of rapid EV chargers. Conversely, suburban areas in the south-east exhibit the lowest accessibility to EV chargers compared to other suburban regions in London.

Integrating calculated accessibility with the two subjective measures—perceived and prospective accessibility—provides a more holistic understanding of accessibility for EV charging infrastructure and services. As shown in Fig. 3b, the 3D scatter plot visualises the relationship between normalised calculated, perceived, and prospective accessibility for each individual. Each point in the plot represents a respondent, with the colour gradient indicating the sum of the three accessibility values—where lighter shades represent higher overall accessibility and darker shades indicate lower overall accessibility. This visualization allows for an intuitive exploration of the degree of alignment or divergence among the three accessibility measures across the sample.

Compared to previous studies such as Lättman et al. (2018), which typically address such discrepancies at an aggregate level, this study applies K-means cluster analysis to the three normalised accessibility measures and spatial locations, enabling the identification of more granular patterns across individual users. The number of clusters was set to four, as the average silhouette value peaked at 0.57 for this solution, indicating an optimal clustering structure. As shown in Fig. 3c, Cluster 1 is characterised by relatively high calculated accessibility, while the other three clusters exhibit notably lower levels of calculated accessibility. However, despite having similar calculated accessibility values, Clusters 2, 3, and 4 differ significantly in terms of their subjective accessibility dimensions. Detailed summary statistics are presented in Table 3. These measures were used to assess the level of (dis)agreement across the three dimensions of accessibility. Specifically, Distinct from prior studies, Cluster 1 **(**Balanced realists**)** demonstrates the highest level of agreement, with relatively close mean values across all three measures and the lowest standard deviation across means (0.1132). In contrast, the other three clusters broadly align with earlier findings of disagreement, albeit with differing patterns. Cluster 2 (Cautious optimists) and Cluster 4 (Confident adopters**)** share a similar pattern, both characterised by low calculated accessibility and higher prospective accessibility than perceived accessibility. Yet, the magnitude of difference is much greater in Cluster 4, where prospective accessibility (0.8261) far exceeds both perceived (0.5224) and calculated (0.1214) accessibility, resulting in the largest standard deviation across means (0.3535). This reflects particularly strong confidence in future charging provision, suggesting that, despite low calculated accessibility, individuals in Cluster 4 may be more inclined to adopt EVs compared to those in Cluster 2. Cluster 3 **(**Present-biased overestimators**)** displays a different pattern: although calculated accessibility is similarly low, perceived accessibility (0.6302) is the highest among all clusters, while prospective accessibility (0.4261) is the lowest. This indicates that current provision is overestimated, but expectations for future accessibility remain cautious.

These findings provide a more nuanced perspective than previous studies, which have broadly acknowledged discrepancies between calculated and perceived accessibility. Our results reveal a spectrum of alignment: from moderate agreement (Cluster 1) to moderate disagreement (Cluster 2), and strong disagreement (Clusters 3 and 4). This highlights the importance of adopting a combined perspective when evaluating accessibility, as users' perceptions and expectations do not always align with modelled measures. More importantly, these findings suggest that the interactions between accessibility dimensions are complex and cannot be generalised. Unlike previous studies that broadly acknowledge a general mismatch between calculated and perceived accessibility, this study explicitly accounts for the interplay of three accessibility dimensions (calculated, perceived, and prospective) and reveals that not all users experience disagreement. In fact, we identified a cluster (Cluster 1) where users demonstrate agreement across all three dimensions. For those clusters where disagreement does exist, the degree and pattern of disagreement vary: some groups experience moderate mismatches, while others show stronger, more pronounced discrepancies. This finer-grained perspective highlights the necessity of adopting a combined accessibility framework that moves beyond generalisations, enabling a more nuanced understanding of accessibility experiences in the context of EV charging infrastructure.

### 4.2. Cluster drivers

Motivated by the need to uncover the key enablers of (dis)agreement, a non-linear modelling approach was adopted to capture the complex interactions between socio-demographic factors, the built environment, travel behaviour, and attitudes. The Random Forest classifier achieved the best performance among the four algorithms, with an overall accuracy of 0.781 and an F1-score of 0.761. This model enabled the identification of the top eight features that contribute most to cluster classification. Recognising the limitations of global feature importance alone, we further conducted partial dependence analyses for these eight features to explore their marginal effects on cluster membership probabilities.

The overall partial dependence patterns reveal both shared trends and cluster-specific differences. First, the partial dependence plots (Fig. 4) reveal that clusters differ in their sensitivity to specific features, as reflected in the steepness of gradients. Cluster 1 (Balanced realists) is strongly influenced by built environment factors such as road density and proximity to major roads, showing steeper gradients and marked

**Table 3**
Summary statistics of clusters.

| Clusters (size) | Mean Perceived Accessibility (SD) | Mean Prospective Accessibility (SD) | Mean Calculated Accessibility (SD) | SD across means | Range across means |
|---|---|---|---|---|---|
| Cluster 1 ($n = 175$) Balanced realists | 0.4621 (0.2080) | 0.5778 (0.2135) | 0.6889 (0.1582) | 0.1132 | 0.2265 |
| Cluster 2 ($n = 325$) Cautious optimists | 0.2178 (0.1385) | 0.5274 (0.1758) | 0.1272 (0.1271) | 0.2098 | 0.4402 |
| Cluster 3 ($n = 308$) Present-biased overestimators | 0.6302 (0.1428) | 0.4261 (0.1512) | 0.1316 (0.1032) | 0.2507 | 0.4987 |
| Cluster 4 ($n = 280$) Confident adopters | 0.5224 (0.1783) | 0.8261 (0.1087) | 0.1214 (0.1057) | 0.3535 | 0.0157 |

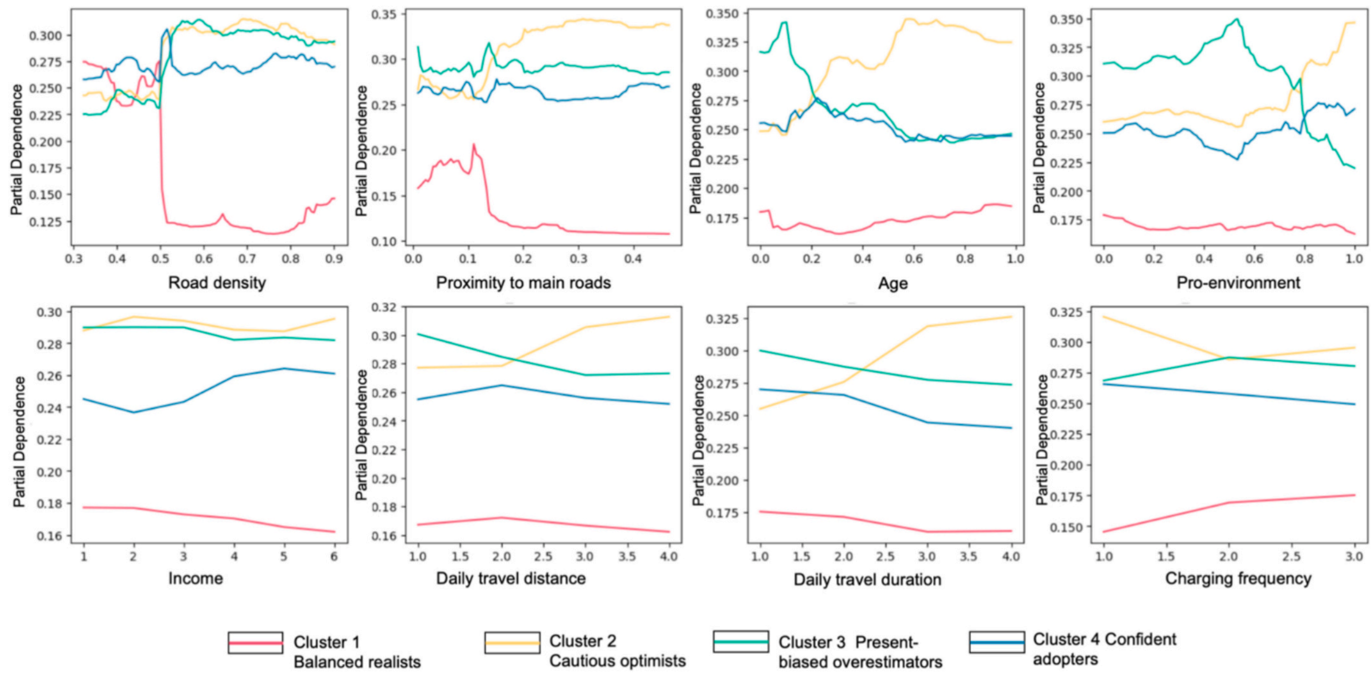


**Fig. 4.** Partial dependence plots for the four clusters including the key features. The x-axis represents the normalised values of each feature, while the y-axis indicates the predicted probability of cluster membership averaged across all individuals.

fluctuations in predicted probabilities as these variables change. Cluster 2 (Cautious optimists) also displays steep gradients for road density and proximity to roads but, in addition, shows strong sensitivity to socio-demographic and behavioural features such as age and daily travel duration. Cluster 3 (Present-biased overestimators) is shaped by both built environment and attitudinal features, particularly pro-environmental attitudes, again reflected in noticeable fluctuations in the partial dependence lines. In contrast, Cluster 4 (Confident adopters) demonstrates relatively flat lines with minimal fluctuations across all eight features, indicating weaker sensitivities and a more stable response to individual factors.

These sensitivity patterns correspond closely to the accessibility mismatches identified in the cluster analysis. For example, the strong responsiveness of Cluster 1 (Balanced realists) to road density helps explain its relatively balanced accessibility profile across perceived, prospective, and calculated measures. The heightened role of pro-environmental attitudes in Cluster 3 (Present-biased overestimators) aligns with its profile of overestimated perceived accessibility but low prospective accessibility. Similarly, the flat and less differentiated lines for Cluster 4 (Confident adopters) reflect its confidence in future charging provision, despite persistently low calculated accessibility.

In addition, behavioural features, particularly average daily travel duration and distance, highlight a sharp contrast between Cluster 2 (Cautious optimists) and Cluster 3 (Present-biased overestimators). For Cluster 2, longer travel durations and distances are associated with a higher probability of cluster membership, aligning with its profile of low perceived but relatively higher prospective accessibility. In contrast, for Cluster 3, longer travel duration and distance reduce the likelihood of cluster membership, indicating that this group is characterised by shorter, more localised travel patterns. This behavioural evidence is consistent with their accessibility profile: shorter travel distances help explain why perceived accessibility is overestimated, while limited willingness to travel further aligns with their low expectations of future accessibility. These contrasting patterns suggest differentiated policy priorities: improving regional connectivity and long-distance charging options may help address the needs of Cluster 2, whereas neighbourhood-based charging provision is critical for Cluster 3 to align perceived and prospective accessibility and sustain confidence in future EV adoption.

## 5. Conclusion

Since 2010, the UK government has emphasised the importance of expanding the public electric vehicle (EV) charging network to support the transition to electric mobility, particularly in urban areas such as London. However, current literature has paid limited attention to accessibility to EV charging infrastructure, especially in terms of integrating subjective dimensions such as perceived accessibility or investigating the factors that contribute to alignment and mismatch between modelled accessibility and user experience. This study proposes a combined accessibility framework that integrates calculated, perceived, and prospective accessibility measures to investigate accessibility to public EV chargers in London. The study places particular emphasis on capturing the nuanced and complex interactions between these three dimensions, aiming to uncover the factors that drive (dis)agreement across them.

This research yields two key findings. First, rather than generalising the relationship between calculated accessibility and subjective accessibility (perceived and prospective accessibility), this study explicitly considers the delicate and complex interactions among them. Different from previous work (Pot et al., 2023; Geurs and Van Wee, 2004) that broadly finds a generic disagreement between calculated and perceived accessibility, this study provides granular insights, revealing a spectrum of alignment across four clusters: while three clusters exhibit moderate to strong degrees of disagreement, one cluster demonstrates moderate agreement across the three dimensions. This nuanced finding reinforces the importance of incorporating different dimensions of accessibility into EV infrastructure planning, as modelled accessibility alone does not always reflect users' perceptions, nor does it necessarily predict actual charging behaviour.

Second, to understand the drivers of the (dis)agreement patterns, the study identifies key factors that contribute to the observed discrepancies. These include built environment characteristics such as road density and proximity to major roads, as well as socio-demographic and behavioural factors such as age, daily travel distance, and daily travel duration. These findings align with previous research (Negm and El-

Geneidy, 2024) but extend the literature by demonstrating how these factors interact within a combined accessibility framework specific to EV charging. Overall, the results highlight how built environment, demographics, and travel behaviours shape accessibility and underscore the need for targeted, cluster-specific policies to address these differences.

This study represents the first attempt to propose a combined framework for evaluating EV charging infrastructure and services. Unlike previous work that has treated perceived and calculated accessibility as separate constructs, this study integrates calculated, perceived, and prospective accessibility to re-examine EV charging accessibility from a user-centric perspective. This approach is based on the understanding that spatial behaviour is influenced not only by the provision of infrastructure but also by the way individuals, shaped by their socio-demographic characteristics, attitudes, and knowledge of the environment, perceive and interpret the available charging infrastructure. The combined framework provides a practical tool for planners and practitioners to assess EV charging provision more holistically. Specifically, it highlights the importance of complementing infrastructure placement with ongoing user feedback to identify potential gaps between provision and user perception. This step is critical for informing future EV charging deployment strategies, ensuring that infrastructure is not only available, but also accessible in ways that reflect users' needs and experiences. For example, placing chargers in locations that are easy to find, navigate, and use within the built environment can help bridge the gap between technical provision and real-world usability, thereby enhancing both the accessibility and overall effectiveness of EV charging networks. This framework has strong potential to scale to other international cities and to be applied to shared transport services such as car clubs. By leveraging emerging big data sources, it enables the integration of infrastructure planning with users' perceptions and expectations, offering a transferable approach that accounts for socio-demographic and behavioural differences across urban contexts.

Although this study provides valuable insights into EV charger accessibility, we encourage future research to explore several directions in greater depth. First, applying the combined accessibility framework to other cities, regions, or national contexts would offer important comparative perspectives. Such cross-contextual applications could reveal how the interplay between infrastructure provision and subjective perceptions varies across spatial and cultural settings, offering richer insights for both theory and practice. Second, further research could investigate the potential of emerging technologies, such as natural language processing (NLP) on user-generated content (e.g., social media posts, reviews, and comments) or feedback collected via local authority digital platforms (e.g., participatory planning apps or digital crowdsourcing tools). Integrating such techniques would enhance the granularity and timeliness of user perspectives (Afzalan and Muller, 2018), enabling a more dynamic and responsive approach to EV infrastructure planning that better aligns with the needs and expectations of diverse user groups. Additionally, comparing different methods for measuring subjective accessibility offers a valuable direction for future research (Van Wee, 2016), helping to assess the consistency and robustness of results across approaches.

## CRediT authorship contribution statement

**Yuerong Zhang:** Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yanghui Cao:** Writing – original draft, Visualization, Investigation, Conceptualization.

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## Appendix A. Appendix

**Table 1**
Hyperparameters configurations and performance metrics of the four models.

| Models | Hyperparameter configurations | Accuracy | F1-score |
|---|---|---|---|
| XGBoost | Number of trees = 500<br>Max depth = 9<br>Learning rate = 0.05<br>subsample: 0.9 | 0.762 | 0.743 |
| MLP | Hidden layers: [100, 50, 50, 50]<br>Activation: ReLu<br>Solver: Adam<br>Learning rate: 0.005<br>Max iterations: 1000 | 0.684 | 0.665 |
| RF | Number of trees = 300<br>Max depth = 12<br>Min samples split = 3<br>Max features = 9 | 0.781 | 0.761 |
| SVM | Kerel = RBF<br>Regularization parameter (C): 1.0<br>Gamma: scale | 0.597 | 0.590 |

## Data availability

Data will be made available on request.

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