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Evaluating the accessibility of on-street household electric vehicle charging stations in London: Policy insights from equity analysis across emission zones

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1. Introduction

In light of the UK's commitment to achieving Net Zero emissions by 2050, coupled with the impending 2035 ban on new diesel and petrol vehicles, the promotion of Electric Vehicle (EV) adoption has become increasingly critical. High accessibility of EV charging infrastructure has been shown critically important to promote the public's intentions to purchase EV (Canepa et al., 2019; Coffman et al., 2017). Recent study also found that the enhanced accessibility to EV chargers improves traffic flow and lower particulate matters (PM2.5) emission levels by 1.3–2.2% (Liang et al., 2023), underscoring the environmental benefits of expanded EV infrastructure. Despite these advantages, the rollout of EV charging facilities, especially public on-street chargers, is progressing at an insufficient pace for certain types of charging points. This slow deployment is rendered even more critical by the fact that over two-fifths (44%) of UK homes, as reported by Lloyds Bank (2022), lack off-road parking, making them unsuitable for home EV charging solutions. This situation is projected to affect approximately 10 million electric cars and vans by 2050, which are regularly parked overnight on the street (HM Government (2022)). To ensure that the UK's transition to electric vehicles is both inclusive and effective, it is imperative to address these challenges.

In recent years, there has been an emergence of studies exploring the accessibility of public EV chargers (Li et al., 2020; Park et al., 2022). These studies specifically aim to examine the placement and deployment of Electric Vehicle Charging Stations (EVCS) from a transport equity perspective, investigating whether vulnerable groups have limited access to EV charging facilities. Despite these valuable insights, there are three major limitations of existing research. First, previous work treats all EV chargers the same with little consideration of the inherent differences among different types of EV chargers, posing a risk of overestimating the EV charging accessibility. In particular, one specific type of EV charger is overlooked, i.e., On-street household charging (also known as on-street resident chargers). Previous empirical studies (Hsu and Fingerman, 2021; Khan et al., 2022) have identified a significant issue regarding the inadequate accessibility of EV chargers for residents of multi-unit dwellings who are unable to install home chargers. In response to this challenge, the provision of on-street household charging provides a solution to residences without home charging and is mainly intended for overnight slow charging near houses and apartments. While in effect, prior empirical studies have revealed a significant EV charging accessibility issue for multi-unit dwellings and some driver groups, that are not able to install home chargers, whereas on-street household charging offers promising solutions.

Second, despite a growing interest in EV charger accessibility, the discussion of EVCS accessibility and its contributing factors remains relatively limited. No study has yet considered the impact of emission control regulations on the accessibility of EVCS. In London, three tiers of Emission Control Regulations play a crucial role: the Congestion Charge Zone (CCZ), the Ultra-Low Emission Zone (ULEZ), and the Expanded Ultra-Low Emission Zone (EULEZ). These regulations significantly influence EVCS accessibility, and understanding their effects can help overcome the barriers to electric vehicle (EV) adoption and inform policy recommendations for enhancing EV uptake. London, as the pioneering city to implement such stringent policies, presents a case whose outcomes warrant thorough investigation. The insights and experiences gained from this could be transferable to other international cities.

Third, current studies tend to involve a priori assumed relationship between EVCS accessibility and some determinants such as percentage of black and low education levels (Roy and Law, 2022; Hsu and

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Fingerman, 2021). However, this approach carries twofold risks. First, it may overlook context-specific factors. For example, while low-income groups may face limited EVCS accessibility in certain areas, there can be spatial heterogeneity across the entire city. Second, these relationships may exhibit non-linear patterns that are difficult for conventional models to capture.

To address these gaps, this study introduces an analytical framework to examine the factors influencing EVCS accessibility and investigate whether these factors differ significantly across three London emission zones. This study is the first to focus on the accessibility of public EVCS, particularly for on-street households that rely heavily on public EV chargers. To ensure an inclusive and effective transition to EV adoption, this study identifies areas and disadvantaged cohorts with limited EVCS accessibility, providing evidence for tailored policy interventions and guidance on the deployment of EVCS.

2. Related works

Accessibility is defined as the potential or possibilities of various opportunities for interaction, i.e., the ease with which interactions can take place, as delineated by Hansen (1959) and subsequently elaborated upon by researchers such as El-Geneidy et al. (2016) and Pereira (2019). The origin of this concept is attributed to Hansen, which sparked a range of developments and interpretations. For instance, Handy and Niemeier (1997) interpreted accessibility in terms of the economic benefits that people derive from access to spatially distributed activities. Similarly, Neutens et al. (2007) posited that accessibility reflects the scope of activities accessible to an individual at a given time. Despite the absence of an agreed definition, Järv et al. (2018) offered an insightful understanding of accessibility, positing it as a combination of three interrelated components: individuals, transport, and activities. These components coexist within a framework of interdependent spatial accessibility, underscoring the multifaceted nature of the accessibility. Depending on the research interest, the field of accessibility has been explored through different combinations of these three components. Investigations have spanned multiple contexts, including the analysis of elderly individuals' walking accessibility to parks (Cheng et al., 2019) and hospitals (Zhang et al., 2022), as well as the examination of low-income groups' access to employment opportunities via public transportation (Deboosere and El-Geneidy, 2018), and the assessment of the public's access to grocery stores through public transport (Järv et al., 2018).

Despite the proliferation of studies on transport accessibility, research on EV charger station (EVCS) accessibility has only started to gain attention since 2021. EVCS accessibility remains in its nascent compared to the broader transport accessibility literature. Current work on EVCS accessibility generally can be categorised into two types in terms of their spatial scale: regional and neighbourhood levels. As the first study to compare regional accessibility, Falchetta and Noussan (2021) examined public EV chargers across European countries and found significant inequalities in their distribution. These disparities persist both across and within countries, despite the considerable expansion and continuous growth of EVCS in recent years. They specifically noted pronounced disparities between Northern and Southern Europe. Further, by analysing the distribution of fast EV chargers along the UK's strategic road network, Pemberton et al. (2021) identified a notable gap in the accessibility of fast EV chargers in rural areas compared to urban areas. This discrepancy poses significant challenges in overcoming range anxiety among EV users. The measurement of EV chargers' accessibility at regional level mainly utilises a set of simple yet effective indicators such as charging points density (Falchetta and Noussan, 2021) and charging points per km (Pemberton et al., 2021). This approach is tailored to achieve a foundational comprehension of their spatial distribution and underlying patterns.

In contrast to the body of studies on EVCS at the regional level, studies focusing on the neighbourhood level within urban contexts are more prevalent. The concentration of current research is particular evident within the geographically scopes of the United States (Hsu and Fingerman, 2021; Roy and Law, 2022; Khan et al., 2022; Carlton and Sultana, 2023; Guo and Wang, 2023), and China (Li et al., 2022; Zhou et al., 2021; Peng et al., 2024). This trend may be attributed to the constraints imposed by open data availability, given that the EVCS infrastructure remains in a nascent phase of development. Within the existing literature on EVCS accessibility, the majority of studies adopt opportunity-based methods to measure accessibility, notably employing Gaussian two-step floating catchment area (G2SFCA) methods. For a more thorough exploration of the metrics employed to evaluate accessibility, one can refer to the detailed analysis presented in the detailed review by Hopkins et al. (2023). Expanding the scope beyond the spatial accessibility, two pioneering studies attempted to measure space-time accessibility of EVCS, thereby acknowledging the dynamic nature of charging demand influenced by economic activities and commuting patterns between work and residence throughout the day. Zhou et al. (2021) examined the accessibility of EVCS at four different time periods over the weekday in Nanjing, China, revealing significant variations in accessibility across different regions, with peripheral suburbs demonstrating the most notable fluctuations. Similarly, Park and his colleagues (2022) measured hourly spatial accessibility over a 24-h period in Seoul, Korea, identifying five distinct temporal clusters.

In the limited yet growing body of research on EV charger accessibility, accessibility has been used as a lens to explore various research topics. These include the relationships between charger accessibility and EV adoption (Nazari et al., 2019; He et al., 2022), the impact of accessibility on housing prices (Liang et al., 2023), and considerations for the strategic placement of EV chargers (Loni and Asadi, 2023; Kłos and Sierpiński, 2023). Among these investigations, a particularly pivotal theme emerging from these studies is the notion of charging equity, or equitable access to EVCS. Transport equity includes, as firstly proposed by Litman (2017), horizontal equity, which treats everyone equally, and vertical equity, which favours tailored support for disadvantaged groups through discounts and special services.

In charging equity, horizontal equity focuses on the spatial distribution of EVCS, assessing the evenness across areas. For example, Li et al. (2022) utilised the Global and Local Moran's I index to evaluate EV charging service capacities in top ten Chinese cities, finding Shanghai to exhibit the highest spatial inequity, unlike Beijing and Hangzhou, which showed no significant spatial disparities, highlighting variations in horizontal equity. Vertical equity, conversely, concerns access disparities for vulnerable groups, such as low-income and elderly cohorts. Studies like Roy and Law (2022) highlight access challenges faced by low-income households, and racial minorities in the U.S., with further analyses on factors such as household income (Peng et al., 2024; Khan et al., 2022), education (Roy and Law, 2022; Peng et al., 2024), Black and Hispanic majority-neighbourhoods (Hsu and Fingerman, 2021), and family composition (Roy and Law, 2022) influencing EVCS accessibility. Given the intricate nature of EVCS accessibility and the multitude of factors influencing its inequity, the analysis extends to the built environment and transportation-related features. This includes examining the impact of housing types, like the rate of multi-unit dwelling units (Hsu and Fingerman, 2021) and government-funded housing (Peng et al., 2024), building density (Roy and Law, 2022), land use mix (Carlton and Sultana, 2023), and proximity to highways (Khan et al., 2022; Hsu and Fingerman, 2021). To gain more comprehensive insights into the accessibility and inequity of EVCS, it has also been prevalent to couple both horizontal and vertical equity. Peng et al. (2024) analysed both types of equity in Hong Kong using spatial autocorrelation and the Gini index. They found that several socio-demographic characteristics, including age, education level, family composition, and housing type, were significantly associated with EVCS accessibility, displaying considerable spatial heterogeneity.

As previously discussed, while existing studies have explored EVCS accessibility and equity, little consideration is given to identifying the underlying factors contributing to disparities or limited access to EVCS. These relationships are frequently simplified using traditional models that rely on linear assumptions. However, it is critical to recognise that the disparities across various geographical areas may be attributed to distinct factors. Indeed, the distribution and accessibility of EVCS are profoundly influenced by transport and energy policies and regulations (Geurs et al., 2010; Wang et al., 2015) such as emission zone, a domain that has been largely overlooked. This gap in the literature highlights the imperative for additional research, particularly focused on uncovering the determinants of EVCS accessibility and their complex, potentially nonlinear relationships with disparities in access. Integrating these considerations, our objective extends beyond merely identifying groups or areas requiring greater attention; it encompasses exploring features linked to low EVCS accessibility. This approach promises to offer nuanced and practical insights for improving the accessibility of EVCS.

3. Methods and data

3.1. Study area and workflow

We illustrate our approach with a case study of three London emission zones (Fig. 1). Initiated in February 2003, the London Congestion Charging Zone (CCZ) Scheme was launched to address to reduce congestion and thus mitigate air pollutant emissions. This scheme imposes a £15 daily charge for vehicle operating within CZZ during specific hours on weekdays, weekends and bank holidays. Building upon this foundation, the Ultra-Low Emission Zone (ULEZ) was introduced by the Mayor of London in 2019. Unlike the CCZ, the ULEZ operates 24 h a day, 7 days a week, aimed at further reducing emissions from the most polluting vehicles. A significant expansion took place on August 29, 2023, with the introduction of the Expanded Ultra-Low Emission Zone (EULEZ), extending the ULEZ across all London boroughs to significantly improve air quality for an additional 5 million residents. Furthermore, the initiative promotes the adoption of zero-emission vehicles by offering a 100% discount on the congestion charge for eligible vehicles until December 24, 2025, thereby encouraging a transition towards more sustainable modes of transportation.

The National Chargepoint Registry (NCR) dataset for public ECVS reveal notable distributions of chargers across the CCZ, ULEZ and EULEZ. Specifically, the CCZ comprises approximately 7.2% of the total chargers, whereas the ULEZ and EULEZ encompass a more substantial portion, accounting for 64.0% and 28.8% of the chargers, respectively. A significant observation is the disparity in the number of slow chargers compared to faster chargers. The dataset indicates that the number of slow chargers is nearly 25 times greater than that of faster chargers across all areas. It is worth mentioning that the total count of faster chargers in the ULEZ and EULEZ areas is approximately the same, while the number of slow chargers in the ULEZ is 2.32 times greater than that in the EULEZ. Furthermore, an analysis of the fast-to-slow charger ratio for each area demonstrates distinctive values. Specifically, the CCZ exhibits a ratio of 0.048, indicating a relatively lower proportion of fast chargers to slow chargers in comparison to the ULEZ and EULEZ. The ULEZ has a fast-to-slow charger ratio of 0.026, while the EULEZ exhibits the highest ratio among the three areas, with a value of 0.071.

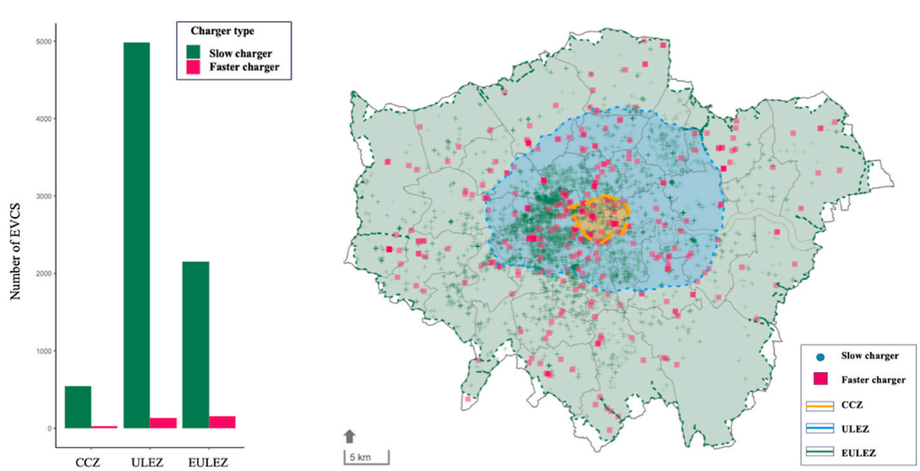
The methods developed in this study proceed through the following steps.

1) Measure the EVCS accessibility at Lower Super Output Area (LSOA) level, which corresponds to neighbourhood level, using Gaussian two-step floating catchment areas (G2SFCA) across the CCZ, ULEZ and EULEZ.
2) Evaluate the generalization performance of four machine learning algorithms—Extreme Gradient Boosting (XGB), CatBoost, Light Gradient Boosting Machine (LightGBM), and Artificial Neural Networks (ANN)—to identify the optimal performer for our analytical context.
3) After identifying the best model, interpret the relative significance of features influencing the accessibility within the three emission zones using the Shapley Additive exPlanations (SHAP) approach.
4) Examine horizonal equity using spatial autocorrelation and assess vertical equity using Gini coefficient approaches.

3.2. Measurement of EVCS accessibility using G2SFCA

To measure the accessibility of EVCS, this study employed the Gaussian two-step floating catchment area (G2SFCA) technique (Luo and Qi, 2009). As shown in Fig. 2, the measurement involves two steps: the first calculates the charger's capacity-to-population ratio, denoted as R_j , The second measures the accessibility for each neighbourhood by aggregating services levels of all EVCS within the catchment areas.

Step 1: The service area of charger location j is defined as the area within 15min 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:



(a) (b)

Fig. 1. Distribution of Slow and Fast Chargers in Three Emission Zones in London. (a) Bar chart showing the Number of Chargers. (b) Spatial Distribution of EVCS.

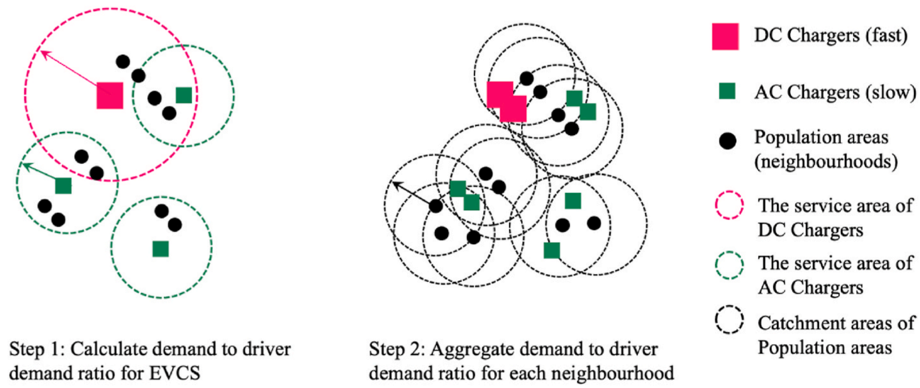


Fig. 2. The Gaussian two-step floating catchment areas analysis for measuring EVCS accessibility.

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

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

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., 2023). 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)*.

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

Step 2: 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. Machine learning

For a comprehensive examination of the accessibility, this study employed Extreme Gradient Boost, an improved gradient boost technique that excels in model performance through optimisation of its loss function and minimisation of tree complexity, thereby mitigating overfitting concerns (Song et al., 2023). The dataset was shuffled randomly and then split into a training set of 80% (4734 neighbourhoods) and a testing set of 20% (1197 neighbourhoods). This study trained models and calculated performance metrics using Scikit-Learn, which is a Python (https://www.python.org/) module integrating a wide range of state-of-art machine learning algorithms. In line with prior work, this study examined 18 features associated with accessibility, encompassing socio-demographic, transport infrastructure, built environment and travel behaviours (Table 1). It is worth noting that we added several new indicators: fuel poverty, public transport accessibility level (PTAL) and transport behaviour indicators to capture the multi-faceted nature of accessibility.

To better compare and identify the best models, we firstly tuned hyperparameters to identify the optimal combinations of parameters that improve the models' performance using a random search technique. Following the fine-tuned models, 10-fold cross-validation (CV) was used to estimate the performance. The advantage of this cross-validation, wherein each fold is used for both training and validation, is that this procedure could yield a lower-variance estimate of the model performance (Stone, 1974). This study adopted three metrics to evaluate model efficacy, i.e., the coefficient of determinants (R^2), the root mean square error (RMSE) and the mean absolute error (MAE), given as:

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{Acc_i} - \overline{Acc_i})^2}{\sum_{i=1}^{n}(Acc_i - \overline{Acc_i})^2} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{Acc_i} - Acc_i,)^2} \tag{6}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{Acc_i} - Acc_i,)^2 \tag{7}$$

The symbols Acc_i, $\widehat{Acc_i}$, $\overline{Acc_i}$ and n indicate for the observed accessibility, predicted accessibility, the mean of observed accessibility and the number of LSOA respectively. Of all the models, this study selects the model yields the highest R^2 values and the lowest MSE and RMSE.

This study used SHapley Additive Explanations (SHAP) to measure the significance of input features to explain the best trained models in three zones. Originating from cooperative game theory (Shapley, 1953), the SHAP value (Lundberg and Lee, 2017) explains the prediction of an instance by computing contribution of each feature to its associated prediction (Tschora et al., 2022). The selection of SHAP is based on the technique's advantages in facilitating model interpretation across multiple scales—namely, the entire model, individual input features, and specific observations (Song et al., 2023), which bridges the gaps between interpretability and accuracy of machine learning. To operationalise this, we calculated both global and local SHAP values using the SHAP python package (https://github.com/shap/shap).

3.4. Horizontal and vertical equity

To provide a more nuanced guidance for the development of EV infrastructure development (Peng et al., 2024), this study examined both horizontal and vertical equity of EVCS accessibility. Regarding horizontal accessibility, the spatial autocorrelation is adopted.

Table 1
Descriptions of influencing factors of EVCS accessibility.

Category	Variables	Description	Data source
Socio-demographic	sd1: Education (Roy and Law, 2022)	The percentage of people whose highest education level is below level 4.	2021 Census Data (ONS)
	sd2: Black percentage (Hsu and Fingerman, 2021)	The percentage of Black/African/Caribbean/Black British	
	sd3: BAME percentage (Hsu and Fingerman, 2021)	The percentage of Black, Asian and minority ethnic.	
	sd4: Household with children (Roy and Law, 2022)	The percentage of household with at least one dependent child.	
	sd 5: Number of cars per household (Roy and Law, 2022)	The average number of car/vans per household.	
	sd 6: Household income (Peng et al., 2024; Khan et al., 2022)	Median annual household income estimate	
	sd 7: Fuel poverty	Fuel poverty in England is measured using the Low Income Low Energy Efficiency (LILEE) indicator.	English Housing Survey 2020 (Department of BusinessEnergy & Industrial Strategy, 2024)
Built environment	be1: Land use mix (Carlton and Sultana, 2023)	$-\sum_j \frac{P_j \times \ln(P_j)}{\ln(J)}$, where P_j is the proportion of developed land in the jth land use type; J is the total number of land use types. This measure is firstly used by Cervero (1988)	OpenStreetMap
	be2: Detached houses percentage (Hsu and Fingerman, 2021)	The percentage of whole house or bungalow.	2021 Census Data (ONS)
	be3: Semi-detached houses percentage (Hsu and Fingerman, 2021)	The percentage of semi-detached.	
	be 4: Terraced house percentage (Hsu and Fingerman, 2021)	The percentage of terraced.	
	be 5: Flat percentage (Hsu and Fingerman, 2021; Canepa et al., 2019)	The percentage of flat, maisonette or apartment.	
	Be6: Tenure	The percentage of tenure owned outright or with a mortgage or loan.	
Transport infrastructures	ti1: Average public transport accessibility levels (PTAL)	A measure indicates connectivity by public transport which used in planning processes in London.	Transport for London
	ti2: The proximity to A Road (Khan et al., 2022)	The distance to the nearest A-level roads.	OpenStreetMap
Travel behaviour	tb1: Working from home percentage	The percentage of people work from home.	2021 Census Data (ONS)
	tb2: Commuting by cars/vans percentage	The percentage of people driving car/vans to work	
	tb3: Distance travelled to work	The average distance travelled to work.	

Specifically, we used Global Moran's I index (Moran, 1950) to measure the overall spatial distribution of EVCS accessibility. The index I_{global}, which ranges from −1 to 1, helps to identify the degree of spatial agglomeration; a higher absolute value indicates a stronger spatial agglomeration, i.e., an uneven spatial distribution of EVCS. Furthermore, we leveraged the local Moran's I index (Anselin, 1995), denoted as I_{local}, to reveal the local spatial pattern of EVCS accessibility, allowing for a detailed examination of EVCS distribution at a more granular level.

$$I_{global} = \frac{n^* \sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i \sum_j w_{ij}{}^* \sum_i (x_i - \overline{x})^2} \tag{8}$$

$$I_{local} = \frac{\sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{9}$$

where n indicates the number of LOSA, x_i, x_j and $\overline{x}$ stand for the accessibility of EVCS at LSOA i and LSOA i, and the mean value of accessibility of EVCS; w_{ij} indicates the spatial weight between LSOA i and LSOA i based on the relative distance.

In terms of vertical equity, Gini coefficient is adopted to examine the level of inequity in accessing to EVCS. The Gini coefficient, which ranges from 0 to 1, indicates perfect equality at 0 and perfect inequality at 1. It is suggested that a Gini coefficient between 0.2 and 0.5 is considered moderate inequality and above 0.5 is considered high inequality (Haidich and Ioannidis, 2004). To accurately assess vertical equity among cohorts with diverse socio-demographic characteristics, this study utilised the refined approach proposed by Peng et al. (2024), which calculates the Gini coefficient for several subgroups. In our analysis, cohorts were categorised into quartiles based on socio-economic variables. For instance, regarding income, the first quartile encompasses communities within the top 25% income bracket, whereas the fourth quartile includes neighbourhoods in the bottom 25% income range. The approach can be presented mathematically by Eq. (10).

$$G_{Q_i} = 1 - \sum_i^{ni} (A_{i+1} + A_i)\left(p_{i+1}^{Q_i} - p_i^{Q_i}\right) \tag{10}$$

where G_{Q_i} indicates the Gini coefficient of the specific quartile Q_i; ni is the set of all LOSA in the quartile; $p_i^{Q_i}$ indicates the populations of the specific quartile at LSOA i; A_i indicates the accessibility at LSOA i.

4. Results and discussion

4.1. Accessibility to EVCS

Fig. 3 illustrates significant spatial variability in the accessibility to Electric Vehicle Charging Stations (EVCS) across the Greater London area. It is apparent that accessibility levels are more pronounced within the central regions, notably within the CCZ. In stark contrast, the peripheries of the city, particularly those lying beyond the ULEZ and EULEZ boundaries, exhibit a diminished availability of EVCS. Notably, the western areas of London within the ULEZ boundary display relatively enhanced EVCS accessibility in comparison to its counterparts. Exceptionally, certain outlying districts such as the vicinities of Stratford and North Greenwich stations showcase elevated EVCS accessibility. These findings align with expectations, given these locations are centres

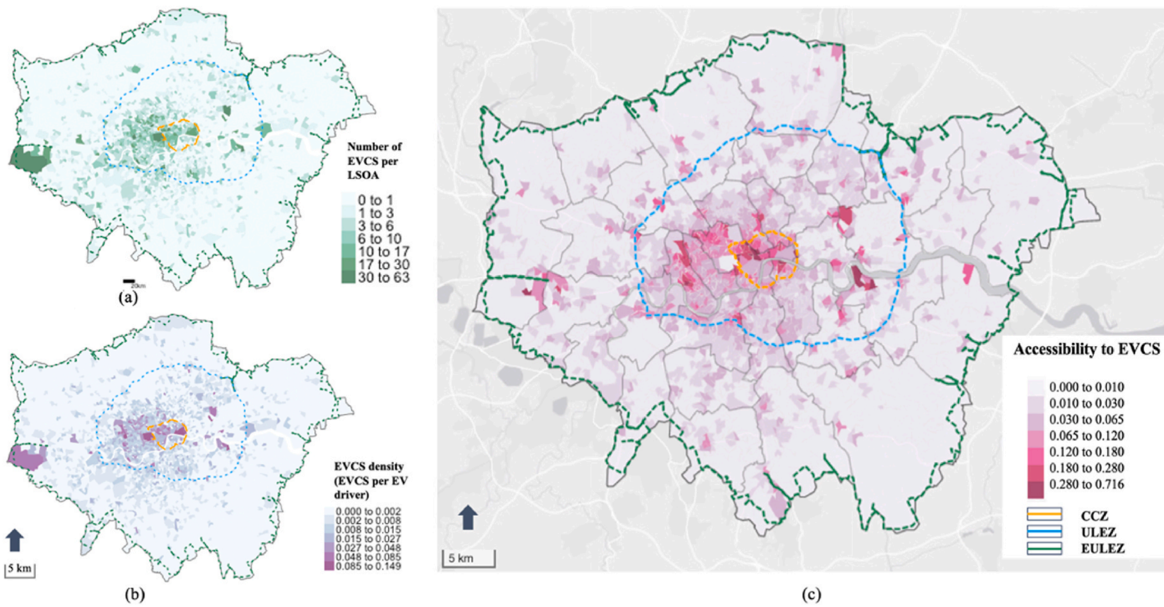


Fig. 3. The On-street Household EVCS Accessibility in London at LSOA levels. (a) The number of EVCS per LSOA. (b) EVCS density indicated by ratio of the number of EVCS to the number of EV drives. (c) EVCS accessibility using G2SFCA.

of recent new urban development and serve as pivotal town centres for North-eastern and South-eastern London. Another noteworthy area of high EVCS provision is the Heathrow Airport vicinity, underscoring its significance as a crucial transport hub.

4.2. Feature importance interpretation based on SHAP

The intersection of socio-demographic, built environmental, transport infrastructures and travel behaviours features delineates the complexity captured by the models. Among the four models evaluated, XGBoost demonstrated the best results for three zones, achieving R-squared values of 0.559, 0.731 and 0.575 for the CCZ, ULEZ and EULEZ respectively. In the comparative analysis of SHAP values across the three zones (Fig. 4), certain features demonstrate significant influence across all emission zones, while others exhibit zone-specific impacts. Notably, PTAL is a common influential feature across the three zones, suggesting a consistent impact of public transport accessibility on the EVCS accessibility irrespective of the zone. Furthermore, features such as fuel poverty and the proportion of BAME majority-neighbourhoods have been identified as key factors in both the CCZ and ULEZ, typically indicating a negative correlation. This could exacerbate existing socio-economic disparities, as the populations in these areas might face additional constraints caused by limited accessibility of EVCS compared to other cohorts. Distinctly, the built environment features diverge across the three zones. In the CCZ, the percentage of flat is a key factor; in the ULEZ, the percentage of detached housing is more influential; and in the ELUEZ, the percentage of terraced housing is of particular importance. These distinctions highlight the relevance of housing types in the analysis of each zone.

In the majority of cases observed in the CCZ, a higher PTAL and a greater proportion of BEME residents are typically associated with increased EVCS accessibility. Conversely, areas characterised by longer average commuting distances, higher levels of fuel poverty, and a greater proportion of households with children are typically associated with reduced accessibility to EVCS. Additionally, the analysis reveals that the impact of certain features, such as the percentage of flats, the percentage of individuals working from home, and the degree of land use diversity, is context-dependent, exhibiting both positive and negative effects on accessibility. Intriguingly, while a higher percentage of black residents may be associated with better accessibility, a larger proportion of BAME individuals has a more mixed or negative association with EVCS accessibility. This highlights a nuanced and multifaceted relationship between demographic factors and access to EVCS.

In ULEZ, as manifested by the highest mean SHAP value, PTAL exhibits a pronounced positive correlation. The analysis further reveals a complex interplay of demographic factors; for instance, the proportion of residents who commute by car and the percentage of BAME individuals display divergent SHAP values, suggesting a multifaceted impact on EVCS accessibility. Particularly, the SHAP values for BAME indicate a tendency towards a negative association, evidenced by a concentration of higher values on the negative side. Additionally, commute distance is inversely related to accessibility, as indicated by the predominance of SHAP values on the left, implying that longer commutes may adversely affect accessibility. Conversely, the proportion of residents working from home and the level of fuel poverty are associated with a mix of both positive and negative impacts, although lower fuel poverty levels appear to positively influence accessibility. Other factors, including the type of housing and land use diversity, also contribute to the model's output, but their impacts vary, underscoring the complexity inherent in predicting EVCS accessibility.

In the EULEZ, the analysis of SHAP values indicates that PTAL is the most significant predictor of EVCS accessibility, with a predominant positive impact reflected by the highest mean SHAP value. Proximity to A roads (primary roads) also emerges as a noteworthy predictor, exhibiting both positive and negative influences on accessibility, albeit with a majority of higher values (red) leaning towards the negative. Other features, such as the percentage of people whose highest education level is below level 4, the percentage of the mode of commuting, residential type, and presence of children, also play roles, yet their impacts are more mixed and do not present a uniform trend across the data.

Based on the observations above, there are two important findings. First, it is found that neighbourhoods suffering from fuel poverty, as well as those with a higher representation of Black, Asian, and Minority Ethnic groups, appear to face disproportionately restricted access to EVCS relative to other demographic cohorts. It would suggest that environmental policies such as emission zones, rather than levelling the playing field, are inadvertently reinforcing existing inequities or even creating new ones. Policymakers would need to address these issues directly to prevent a compounding of disadvantage and ensure that environmental benefits do not unequally burden already marginalized

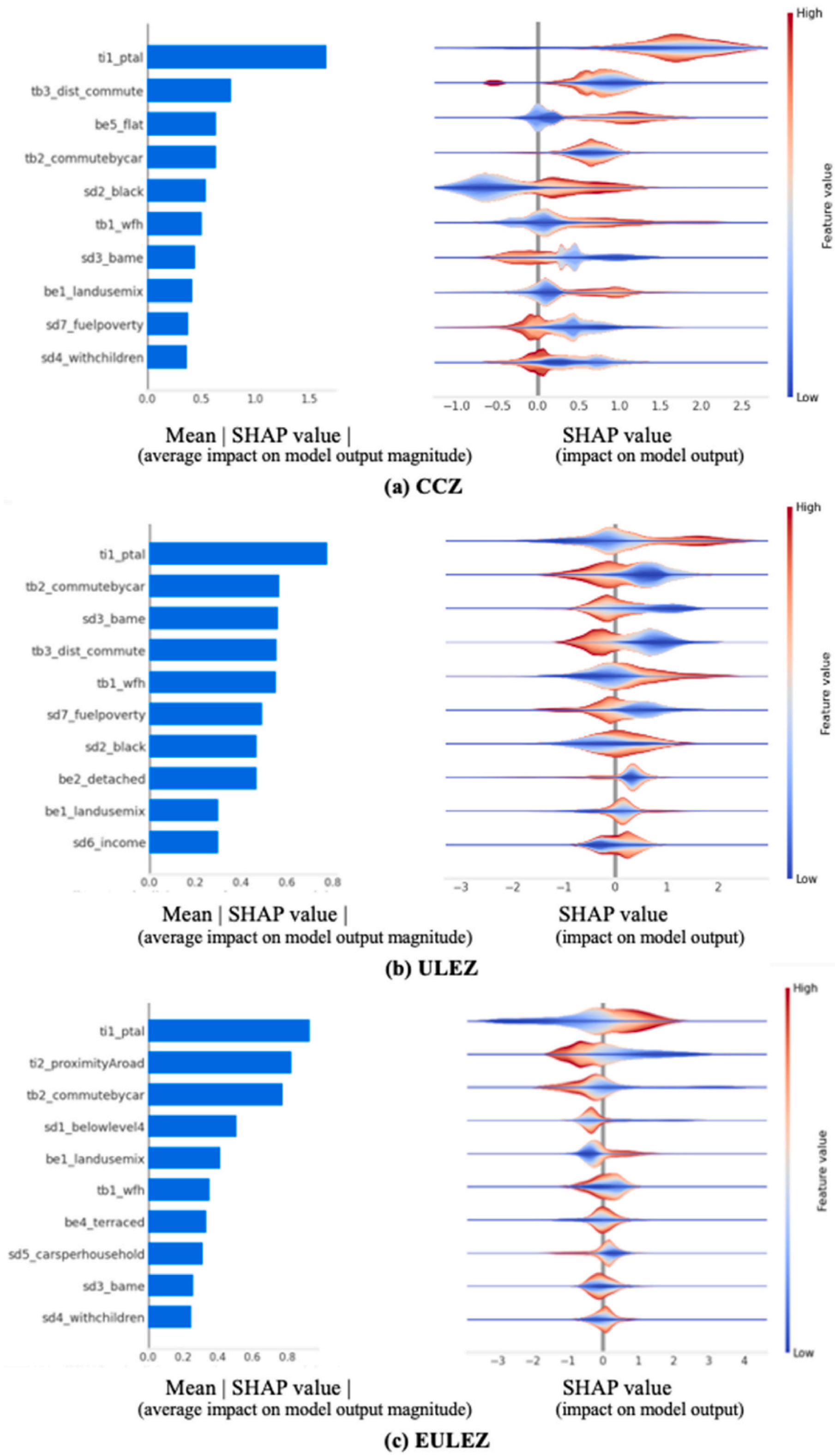


Fig. 4. SHAP feature importance. (a) The mean absolute SHAP values of features. (b) SHAP violin plot summarising the top ten features.

neighbourhoods.

Second, a counterintuitive correlation was observed within the EULEZ: public transport accessibility and EVCS accessibility are positively associated. Regions with low public transport accessibility, which presumably have a higher reliance on vehicles, exhibited lower EVCS accessibility. This finding challenges the expected paradigm wherein areas with diminished public transport services, hence a higher dependency on personal vehicles, would necessitate and thus possess a higher provision of EV charging infrastructure. This discrepancy invites a critical discussion regarding the implications for transport planning and environmental policy. It suggests a potential misalignment between the objectives of enhancing public transport accessibility and promoting electric vehicle adoption through adequate charging infrastructure. Policy adjustments should be required to ensure equitable EV charging access across varied public transport accessibility levels, fostering a more inclusive approach to promoting electric vehicle usage.

4.3. Focusing on equity

In examining the spatial equity of accessibility, the Global Moran's I statistic serves as a critical measure for assessing spatial autocorrelation. The analysis reveals a Global Moran's I statistic of 0.608 ($P < 0.01$) in London, indicating significant positive spatial autocorrelation. This suggests that the areas with similar levels of EV charger accessibility tent to cluster together, pointing to unequal distribution of chargers, where some areas are well-served while others are lacking. Besides, this value notably surpasses the empirical findings from studies conducted in other urban areas, such as Hong Kong (Peng et al., 2024), where the statistic was recorded at 0.275 and Shanghai at 0.054 (Li et al., 2022). Such a discrepancy highlights a pronounced spatial disparity in the distribution of EVCS within London, suggesting a more acute challenge in spatial equity related to EVCS accessibility when compared to the aforementioned cities.

The ULEZ exhibits a Global Moran's I value of 0.654, signifying a pronounced tendency for areas with similar accessibility values to cluster spatially. This suggests a relatively high level of spatial inequity. As shown in Fig. 5, Central and West London within the ULEZ are characterised by concentrated pockets of high accessibility. The blue areas (High-High Cluster) indicate regions of high accessibility that are also surrounded by areas with high accessibility. In contrast, the Eastern regions within the ULEZ (delineated as the Low-Low Cluster and depicted in orange) exhibit a significant agglomeration of areas characterised by low accessibility with a few exceptions. Specifically, new development areas such as Stratford and North Greenwich deviate from this trend, presenting higher levels of accessibility.

Compared to the ULEZ, the CCZ and EULEZ indicate relatively modest level of spatial agglomeration of accessibility within these zones, with Global Moran's I values of 0.322 and 0.243, respectively. Such findings imply that there are minor disparities in accessibility across different areas, suggesting a more evenly distributed spatial equity of accessibility. It is noteworthy that the relatively even spatial distribution of accessibility in the EULEZ may be attributable to an overall lower level of accessibility when compared to other zones.

The preceding analysis revealed that areas characterised by a higher proportion of BAME populations and households grappling with fuel poverty within the CCZ and ULEZ tend to exhibit limited accessibility in comparison to other cohorts. To substantiate the vertical inequity, this study calculated the Gini coefficient and plotted the Lorenz Curve (Fig. 6). Specifically, within neighbourhoods predominantly comprised of BAME individuals (4th Quartile, where the BAME population exceeds 54.12%), the Gini coefficients are recorded at 0.420 and 0.669 for the CCZ and ULEZ, respectively, highlighting substantial disparities in equity. Similarly, the analysis extended to cohorts affected by fuel poverty (4th Quartile, with over 13.95% of households classified under fuel poverty within these communities). Furthermore, as shown in Table 2, it is found that transport equity issues are more pronounced in the ULEZ compared to the CCZ. For example, the Gini coefficient for fuel poverty in the ULEZ reaches 0.634 at the 4th quartile, whereas it is 0.455 in the CCZ, indicating greater inequality in energy poverty distribution within the ULEZ. A similar pattern is observed for BAME populations, with the ULEZ showing a higher Gini coefficient (0.669) compared to the CCZ (0.420).

5. Conclusion and policy implications

5.1. Conclusions

As EVCS accessibility plays a critical role in promoting the adoption of EVs, it becomes imperative to scrutinise how charging infrastructure can be deployed to accelerate efficient and inclusive development of on-street solutions for residents without driveways. This work examines the accessibility of on-street public EVCS across three emission zones in London using a combined approach of explainable machine learning and geospatial analysis. Our research presents a framework to determine whether the factors affecting accessibility differ significantly across the Congestion Charge Zone, the Ultra-low Emission Zone, and the Expanded Ultra-low Emission Zone. To accurately identify underserved areas and the cohorts in need of attention, this research also conducts an equity analysis.

There are three key findings. First, the determinants influencing

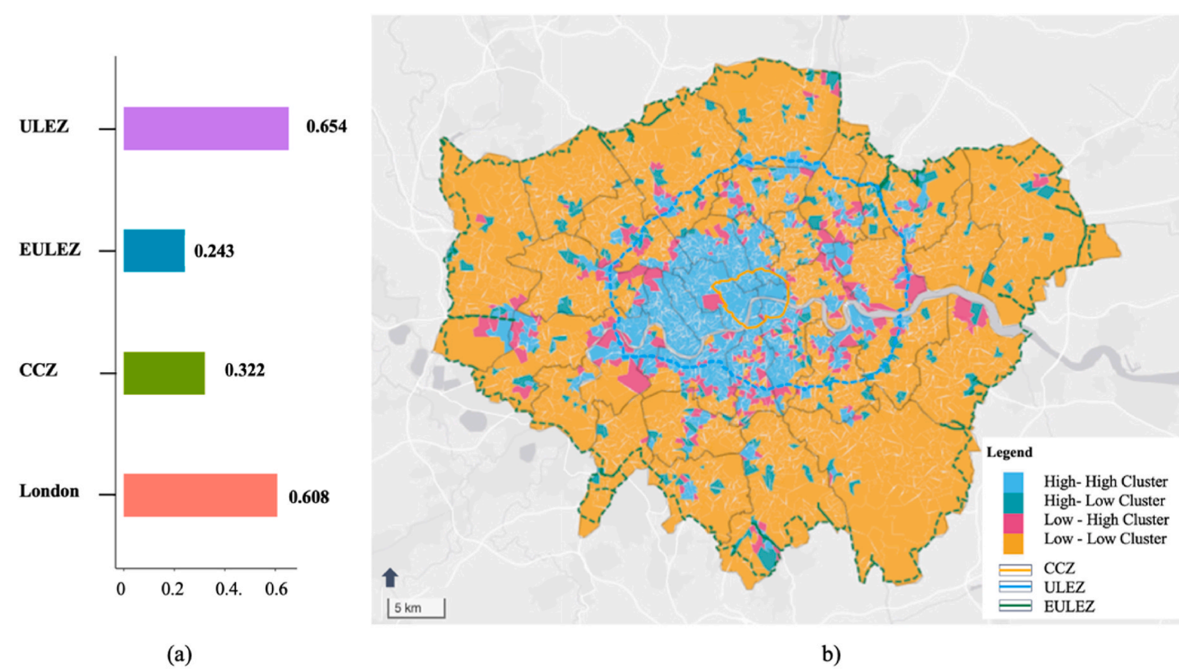


Fig. 5. Spatial agglomerations of EVCS accessibility. a) Global Moran I across zones. b) The four clusters based on Local Moran I.

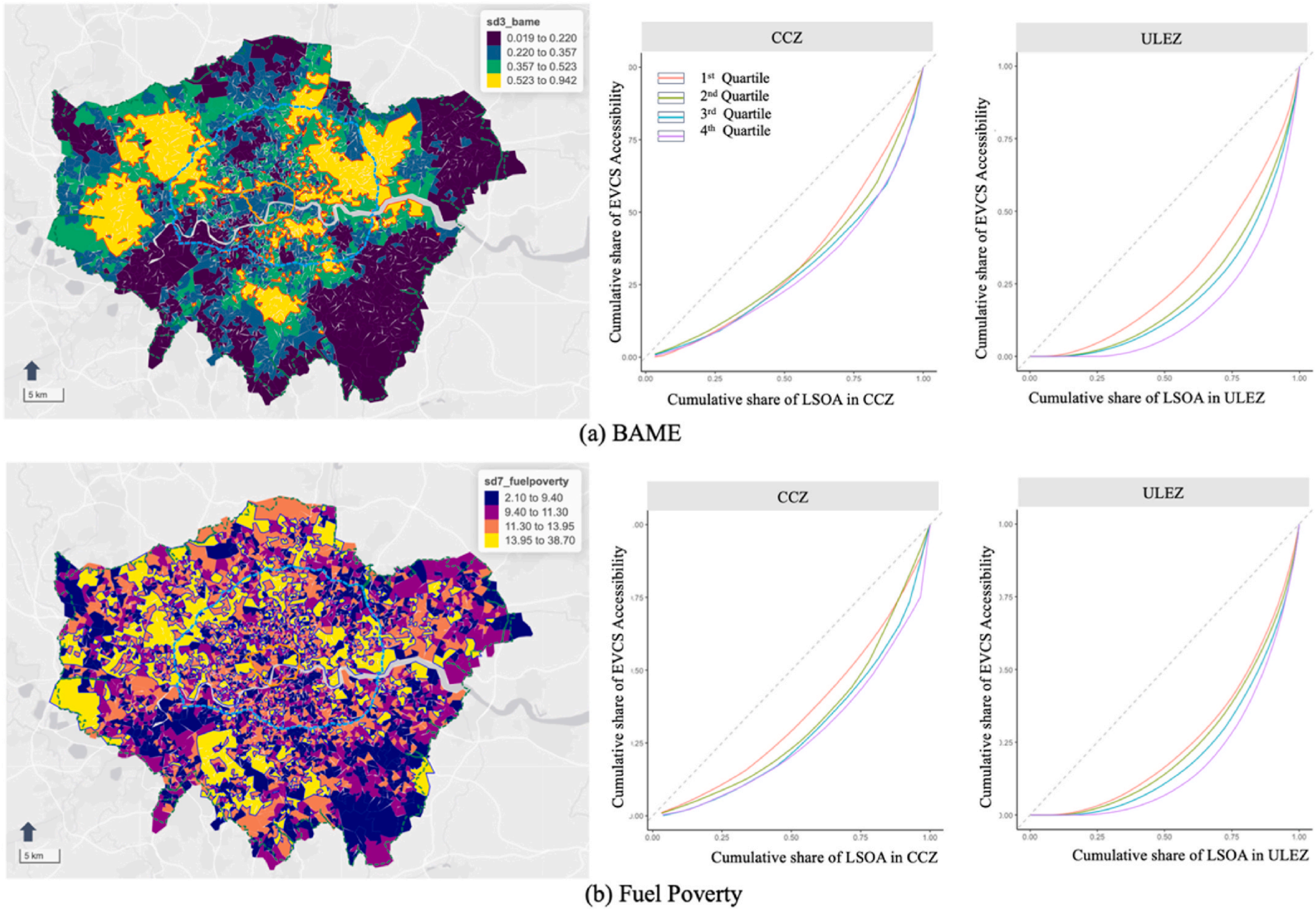


Fig. 6. The Gini coefficient and the Lorenz curve for assessing access to all EV charger types across subgroups.

Table 2
Comparing the Gini coefficient within the CCZ and ULEZ.

		1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
Fuel poverty	CCZ	0.303	0.368	0.423	0.455
	ULEZ	0.494	0.527	0.580	0.634
BAME	CCZ	0.333	0.348	0.401	0.420
	ULEZ	0.434	0.541	0.581	0.669

EVCS accessibility vary significantly across the three emission zones, indicating a zone-specific characteristic. For instance, in the CCZ, key factors include commuting distance and the proportion of flats. The percentage of car commuters and BAME populations stand out in importance in the ULEZ; while in the EULEZ, access is notably associated with how close major roads are and the rate of car commuting. Second, a pronounced uneven geographical distribution of public EV chargers is observed in London, with a value of 0.608 (Global Moran's I statistic) signalling significant spatial inequity. The ULEZ exhibits a notable concentration of high-accessibility areas in its central and western areas, contrasted by clusters of low accessibility in eastern London. Besides, compared to other zones, the EULEZ shows a substantial gap in readiness for electric vehicles adoption due to its limited EVCS accessibility. Third, communities predominantly composed of BAME individuals and those grappling with fuel poverty have limited EVCS accessibility compared to other cohorts.

Our study contributes to the existing body of knowledge in several ways. First, this is the first attempt that examines accessibility of EVCS across three emission zones, emphasising its significance on multiple fronts. On one hand, the factors influencing accessibility exhibit substantial spatial variation, particularly in international metropolitan cities characterised by pronounced spatial heterogeneity. On the other hand, emission zones, being implemented in distinct stages, exert unique impacts. Our research underscores the importance of investigating accessibility and its determining factors across diverse zones. Second, diverging from conventional approaches that commence with predefined hypotheses followed by equity analysis, we firstly identified the characteristics of vulnerable groups through interpretable machine learning and then investigated the context specific vulnerable cohorts in vertical equity analysis. Third, our first-hand evidence regarding the accessibility of EVCS offers solid, multifaceted policy implications for three distinct zones. These findings guide the development of electrification strategies and infrastructure investments, ensuring an efficient and equitable transition. Of particular note, we introduce reservations regarding the readiness of households residing in the EULEZ for the transition to electric vehicle (EV) electrification.

5.2. Policy implications

The following strategies should be considered when translating our findings into effective policy implications. First, emission zone-specific subsidies and incentives are required to address the unique needs of each emission zone. For the Congestion Charge Zone (central London), more attention should be paid to multi-unit dwelling areas with limited conditions for installing EV chargers. Greater London Authority should guide local authorities to expand the availability of public charging stations, such as streetlight and kerbside chargers near multi-unit dwelling buildings. Additionally, there is a need to introduce state-of-the-art solutions such as community EV charging (Charly et al., 2023), which facilitate the use of private EV chargers among multiple users. In the Ultra Low Emission Zone, prioritising the deployment of EVCS in residential and commercial areas is crucial to ensuring more equal access for a diverse population. The Expanded Ultra Low Emission Zone reveals a substantial gap in readiness for electric vehicle adoption, further aggravated by the zone's deficiency in public transport and EV charging infrastructure. To address these constraints, the emission zone should prioritise improving accessibility to public transport services, such as increasing underground services and introducing new bus routes.

Second, underserved zone regulation is required. To do so, local authorities should mandate a minimum percentage of changepoint provisions in new developments and major refurbishments, particularly in underserved areas such as eastern London and the Expanded Ultra-low Emission Zone. For example, the London plan (Greater London Authority, 2021) currently mandates that any developments or major refurbishments that require planning should provide more than 20% chargepoint provisions. However, this requirement applies uniformly across London. Our research suggests that this regulation could be adjusted by specifically increasing and tightening chargepoint provision requirements in underserved areas. This targeted regulation will help to ensure that these areas receive adequate charging infrastructure, thereby promoting swift transition to EV adoption. Furthermore, financial subsidies such as low-interest loans and grants could be considered for underserved areas. For local authorities to achieve even spatial distribution and access, it is necessary to regularly monitor and conduct analyses to identify underserved areas using data-driven approaches to guide policy interventions.

Third, policy interventions should include inclusivity and equity. To address the limited EVCS accessibility in neighbourhoods with higher percentages of BAME populations and households suffering from energy poverty, a range of policy interventions is necessary. Primarily, given the more severe equity issues observed in the ULEZ, policymakers should prioritise interventions in vulnerable neighbourhoods identified in this study. These interventions could include targeted subsidies and equity-focused incentive programs. Furthermore, drawing inspiration from California's approach, outreach programs should be implemented to diversify EVCS access and introduce a Low-income EV Charging Programme (Canepa et al., 2019). As a first step, policymakers should establish equity guidelines and metrics to effectively identify disadvantaged communities, thereby aiding informed decision-making. Additionally, engaging with these disadvantaged groups through focused outreach efforts will help policymakers understand the primary barriers and preferences of these communities. These interventions should not only focus on installing public EV chargers to increase accessibility but also consider introducing tiered pricing for EV charging to promote equitable and inclusive access. Additionally, regular monitoring and evaluation of transport equity in public EV charger accessibility are essential for enabling local authorities and transport planners to effectively address equity issues and make necessary course corrections. This is particularly important as the dynamics between EV charging demand and supply evolve rapidly during this transport electrification transition phase. Implementing these strategies will help mitigate inequities and foster a more inclusive shift toward electric vehicles.

Our study has limitations, which open new venues for future research. For further work, we propose the expansion of this research to encompass additional urban and rural areas. Given that the barriers may differ significantly, a wider geographical analysis of EVCS accessibility and its influencing factors could offer more profound insights into the transition challenges. Furthermore, future studies could enhance the understanding of accessibility by integrating charging monetary costs into the accessibility and inequity framework, and by also considering the nuances between actual and perceived accessibility.

CRediT authorship contribution statement

Yuerong Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Maria Kamargianni:** Writing – review & editing, Writing – original draft, Conceptualization. **Long Cheng:** Writing – review & editing, Writing – original draft, Conceptualization. **Jonas De Vos:** Writing – review & editing, Writing – original draft, Conceptualization. **Mengqiu Cao:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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