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Integration of e-scooter sharing with public transit on employment accessibility and equity

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ABSTRACT

E-scooter sharing (ESS) is an emerging shared micro-mobility that may enhance urban travel accessibility. This study investigates the potential of ESS used as the feeder to public transit to improve accessibility compared to sole public transit. Meanwhile, the relationships among accessibility gains, the built environment, and socioeconomic distributions are investigated based on multi-source big data. An empirical analysis in Gothenburg of Sweden demonstrates that ESS can substantially enhance accessibility within a 30-minute travel time, with 15% of areas showing statistically significant benefits. Moreover, the accessibility gains exhibit complex nonlinear relationships with the built environment and socioeconomic. High-income and native-born communities obtain an average of 80% accessibility gain, over 10% higher than other demographic groups. Some areas with significant concentrations of low-income and foreign-born populations rely on public transit but currently lack ESS to improve accessibility. Introducing ESS in these under-served areas could yield up to 143% accessibility gains.

1. Introduction

Electric scooter sharing (ESS) has gained popularity worldwide as a convenient and sustainable mode of micro-mobility due to its various benefits. With electric-powered engines and compact designs, e-scooters provide an eco-friendly and efficient way to navigate busy streets, especially during peak hours or congested areas. Beyond their practicality, ESS plays a crucial role in addressing several traffic-related concerns, such as traffic congestion and pollution (e.g., greenhouse gases) resulting from the rising number of motor vehicles. Similar to other shared micro-mobility such as shared bicycles, ESS can effectively help with first- and last-mile transport challenges and facilitate door-to-door trips (Yan et al., 2023; Mustapha et al., 2024). Notably, ESS are typically dockless, offering greater flexibility than docked systems as they do not restrict pick-up and drop-off locations (Li et al., 2022). Furthermore, e-scooters are lighter and more maneuverable than traditional bicycles, making them particularly user-friendly for those who have difficulty maintaining balance (Li et al., 2024). Additionally, their built-in electric power systems eliminate the need for physical exertion, making them more accessible to a broader range of users, including those who may not feel comfortable riding a bike. This low-effort design is especially advantageous in hilly areas or for longer-distance travel. Consequently, despite being introduced in 2017, much later than free-floating bike-sharing, ESS has experienced rapid expansion and development within

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just a few years (Christoforou et al., 2021). This accelerated adoption has led to ESS becoming an integral part of the transport ecosystem in many cities. Therefore, studying the relationship between ESS and other modes of transport and their impacts on urban mobility is crucial for further sustainable development of ESS in various urban contexts.

Due to the positive impact of shared micro-mobility on promoting the mobility and accessibility of urban public transit, recent years have witnessed a surge in research on shared micro-mobility and their relationship with public transit (Yan et al., 2021). These studies have investigated various facets such as spatiotemporal patterns, accessibility, determinants, and equity of shared micro-mobility (Zuo et al., 2020; Li et al., 2022; Abouelela et al., 2024; Su et al., 2024; Emami and Ramezani, 2024). However, most of these research focused on bike-sharing systems, with limited attention given to ESS (Li et al., 2024; Cheng et al., 2024a). Although some relevant studies have indicated that ESS sharing may complement public transit and thus effectively expand mobility options (Guo et al., 2023), few have quantitatively explored the extent to which ESS enhances access to opportunities, particularly when integrated with public transit as a first- and last-mile feeder. Accessibility, commonly defined as the ease with which individuals can reach desired destinations and activities, is a crucial concept of urban transport planning and policy-making (Santana Palacios and El-Geneidy, 2022). It is a potent predictive indicator for long- and short-term transport decisions, constituting a fundamental prerequisite for designing equitable transport systems (Abouelela et al., 2024). For instance, employment accessibility delineates the extent of job opportunities reachable from a specific location by selecting a particular transport mode, highlighting the ability to engage in employment activities.

Hence, investigating the accessibility gains brought by ESS and their relationship with built environment attributes, such as road density and land use characteristics, is essential for transport practitioners and urban planners (Cheng et al., 2024b). Such quantitative analysis can provide deeper insights into the potential of ESS to enhance urban mobility and inform more effective planning and policy decisions.

Another significant research gap pertains to the equity issue in ESS services. Despite their potential to revolutionize urban mobility, specific population segments face barriers to accessing these services due to various factors, including limited road infrastructure, affordability concerns, and lack of smartphone access (Dill and McNeil, 2021). These challenges are particularly pronounced among disadvantaged populations residing in low-density suburban areas, where the benefits of ESS may not be fully realized. However, the current landscape of ESS services, primarily dominated by profit-driven private entities, may inadvertently exacerbate existing inequalities (Su et al., 2024). Operators may prioritize high-density urban areas with higher profitability, leaving suburban and economically disadvantaged areas under-served. Moreover, the rapid emergence of ESS has outpaced efforts to comprehensively examine their equity implications. As a result, there is a pressing need for research and policy interventions to address these disparities and ensure that ESS benefit all segments of society equitably.

This study aims to examine how integrating ESS with public transit can enhance job accessibility, shape urban spatial and socioeconomic disparities, and relate to the built environment. This study takes Gothenburg as the case, the second-largest city in Sweden, where immigration creates profound divides in their spatial distribution. Specifically, this study attempts to address the following three research questions (RQ).

- RQ1: To what extent urban accessibility can be improved by integration of ESS and public transit, and how is the accessibility benefit spatially distributed?
- RQ2: What built environment factors can potentially account for the accessibility benefits brought by the integration of ESS and public transit?
- RQ3: How are accessibility gains distributed among different socioeconomic groups and is there a discernible tendency in this distribution?

By answering the three research questions, this study advances the literature on transport accessibility and equity related to ESS. This contributes to previous research by investigating the potential for ESS services to enhance urban accessibility when integrated with public transit as a first- and last-mile feeder. This is particularly pertinent given the increasing collaboration between transit agencies and shared micro-mobility companies to enhance accessibility for transport-disadvantaged populations in under-served suburban areas. Additionally, this paper contributes to the growing body of empirical evidence on how ESS services influence transport accessibility and equity, offering new insights from the Nordic context to complement the predominantly US-focused studies.

2. Literature review

2.1. The role of e-scooter sharing in urban transport and accessibility

The potential of micro-mobility to enhance urban transport accessibility has been extensively discussed in the literature (Christoforou et al., 2021; Yan et al., 2023). Micro-mobility offers a more flexible and faster option for short-distance travel compared to walking, and even to cars in congested conditions (Noland, 2019). It also serves as an alternative for walking as the first and last leg connecting to public transit, effectively helping first- and last-mile challenges (Milakis et al., 2020). Among micro-mobility options, ESS have become a promising complement to public transit and continue to gain popularity. For instance, a 2019 survey in San Francisco reported that nearly 30% of respondents and 18% of ESS riders utilized e-scooters as a mode of connecting with public transport (San Francisco Municipal Transportation Agency, 2019). Similarly, in the Chicago area in 2020, over 30% of survey respondents were found to use ESS to access transit stations such as buses and metros (Chicago Department of Transportation, 2020). Yan et al. (2023) conducted surveys in Washington, D.C., and Los Angeles, revealing that ESS can enhance the attractiveness of public transit and substitute driving trips. Current users are more inclined to use ESS as a last-mile connection to public transit.

These survey-based studies provide detailed access to users' socioeconomic attributes, aiding managers in obtaining more granular guidance. However, they will face challenges in scaling to broader urban contexts. As a result, they fail to systematically comprehend how ESS shape urban transport from a macro perspective, particularly regarding accessibility. Unfortunately, quantitative research is scarce on the accessibility contribution of ESS. Liu and Miller (2022) confirmed the positive effect of ESS on public transit accessibility, highlighting the significant benefits of ESS as a first-mile feeder compared to their last-mile counterpart in Columbus. They measured accessibility increments by assessing travel time savings, providing insights from the user's perspective. In contrast, place-based accessibility measures (such as increased opportunities) are more suitable for evaluating the contribution of shared e-scooters to the entire urban transport network (Abouelela et al., 2024). Also, it is noteworthy that national contexts vary, with most studies on ESS accessibility focusing on U.S. cities, while empirical evidence from the Nordic context remains limited.

2.2. Built environment determinants on the integration of micro-mobility and public transit

A strand of studies has substantiated the impact of built environment attributes on urban mobility, specifically about the integration of shared micro-mobility and public transit (Bi et al., 2024; Li et al., 2024). For example, Cheng et al. (2022) used a quantile regression approach to decipher the influence of built environment factors on integrating free-floating bike-sharing with urban rail transport. Their empirical results verified the nonlinear effects of built environment factors, with the length of minor roads around stations exhibiting a strong association with integration usage at low-quantile stations. In addition, residential land use attributes, which are closely related to daily commuting, were found to positively and nonlinearly encourage the integration of bicycles with the metro (Wu et al., 2021; Wang et al., 2022). Similarly, commercial land use was also shown to promote this integration (Ji et al., 2018). Bi et al. (2024) categorized land use patterns and employed multi-variate linear regression to identify influencing factors, revealing that land use patterns related to work and residence facilitated the bicycle–metro integration. These studies predominantly focus on bicycles as micro-mobility feeders connecting to public transit, whereas relatively fewer studies have investigated the integration of ESS. A recent study by Li et al. (2024) conducted a large-scale analysis, utilizing a random forest method to examine the relationship between built environment factors and the integration ratio of ESS with public transit as first- and last-mile solutions in 124 European cities. Their findings revealed that most built environment factors have noteworthy and nonlinear effects, particularly the density of public transit stations.

In summary, existing research consistently demonstrates the significant and nonlinear impact of the built environment on the integration of shared micro-mobility with public transit, with particular emphasis on those land use attributes related to residents' daily commuting. It is worth noting that these studies mainly focus on the integrated usage of shared micro-mobility in conjunction with public transit, while providing a limited account of accessibility (Bivina et al., 2020; Liu and Miller, 2022). Few studies have considered how the built environment affects the accessibility gains provided by the emerging shared micro-mobility.

2.3. The inequitable use of micro-mobility

Micro-mobility services may create barriers for certain segments of the population, collectively identified as the socially excluded group. This exclusion of users may limit the overall benefits of ESS in promoting public transport usage. For instance, individuals without access to smartphones or bank accounts will face challenges using phone-based ESS services (Abouelela et al., 2024; Su et al., 2024). Additionally, retired individuals and older adults who are not technologically proficient are less likely to adopt ESS, with most users being younger, highly educated populations (Mitra and Hess, 2021). This unequal usage, driven by socioeconomic factors (or user characteristics), can be termed social inequality. On the other hand, spatial inequality arises due to the uneven geographical distribution of micro-mobility access. Studies have shown that free-floating micro-mobility can provide more geographically equitable services than docked ones due to their flexibility (Brown et al., 2021). In Washington D.C., low-income and minority groups living in less dense suburban neighborhoods lack sufficient access to micro-mobility services (Ebrahimi et al., 2022). A similar phenomenon can also be observed in the Austin ESS program (Bai and Jiao, 2021). These under-served areas, which lack adequate transport to access other opportunities, are called disadvantaged communities. Such inequity issues lead to insufficient well-being, a critical concern that transport planners strive to rectify. Su et al. (2024) pointed out that while ESS may offer higher accessibility than shared bicycles, they are less effective in promoting equity programs to foster usage among low-income groups. Moreover, a test in Kentucky indicated that disadvantaged communities did not significantly benefit from ESS compared to the rest of the population (Abouelela et al., 2024).

Although numerous studies have investigated equity issues in ESS services, most of them have primarily focused on the equity of ESS usage as a standalone mode of transport, with limited consideration given to the equity of the accessibility gains resulting from their integration with public transit. In other words, the extent to which various demographic groups benefit from improved accessibility due to the introduction of ESS remains unclear. Additionally, due to variations in urban contexts (including demographics, distribution, and geography) across countries and cities, equity programs also differ, resulting in a shortage of empirical evidence regarding socio-spatial equity in the Nordic context.

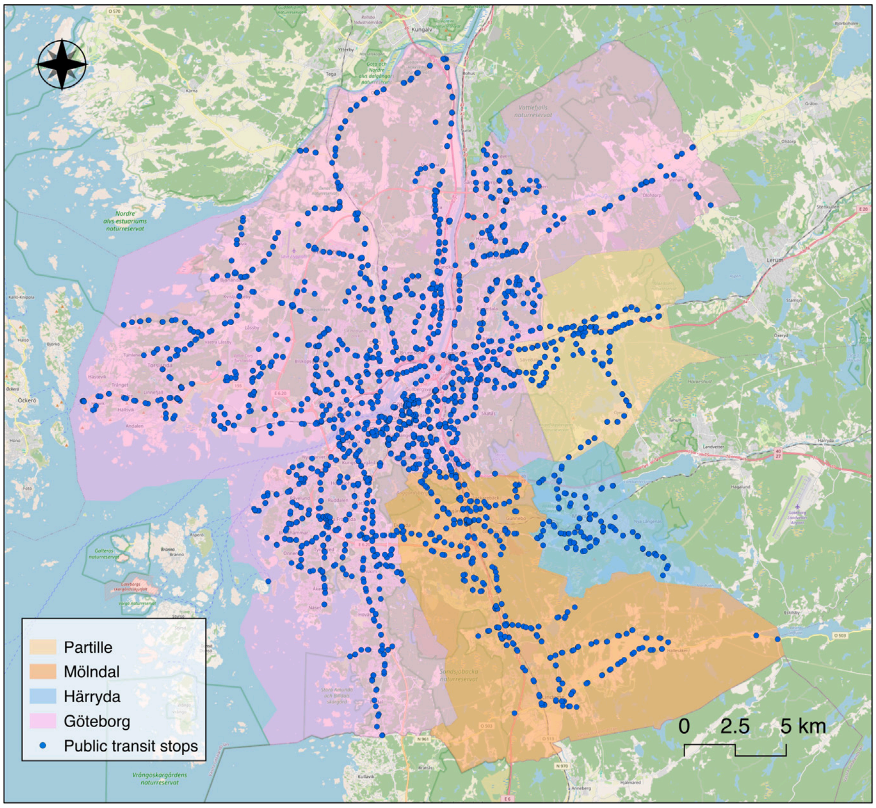


Fig. 1. Study area including Gothenburg (Göteborg) and its three surrounding municipalities. The basemap is sourced from OpenStreetMap (https://www.openstreetmap.org).

3. Study area and data preparation

3.1. Study area

The main study area of this study is Gothenburg, the second largest city of Sweden, positioned midway between Copenhagen and Oslo, making it an important hub for trade and transport. It covers an area of approximately 450 km^2, characterized by a mix of urban and suburban areas, as well as a significant amount of green spaces and waterways. As of 2024, Gothenburg has a population of over 630,000, with around 22% foreign residents (World Population Review, 2024).

In Gothenburg, public transit plays a pivotal role in facilitating mobility for its residents. With over 160 bus routes, 13 tram lines, and frequent ferry services, Gothenburg ensures convenient access to different parts of the city and its surrounding areas. Considering a significant number of commuting patterns from adjacent regions to the Gothenburg area, we also include three surrounding municipalities of Mölndal, Partille, and part of Härryda in the study area, as illustrated in Fig. 1.

In recent years, Gothenburg has embraced ESS usage. The adoption of ESS is driven by their convenience for short trips and as a complement to the existing public transport system. Besides, the extensive network of bike lanes and pedestrian-friendly streets also provide safe and convenient pathways for ESS riders. A relevant study indicated that in 2022, Gothenburg amassed over one million ESS trips supplied by private companies such as VOI and TIER (Almlöf, 2023). The suitable urban layout, environmental consciousness, governmental support, and such abundance of usage data render the Gothenburg area a compelling region for studying ESS accessibility and its implications for urban mobility.

3.2. Data description and preparation

3.2.1. Accessibility-related: hexagon-level origins

The data utilized in this study are derived from various sources. The demographic statistical areas (DeSO)[1] are used to determine the geographical boundary of study area, which is a regional breakdown created by the Statistics Sweden in January, 2018. It

[1] https://www.scb.se/en/services/open-data-api/open-geodata/deso--demographic-statistical-areas/.

Table 1
Descriptive statistics of census data within each square grid.

Attributes	Min	Max	Mean	STD
Job opportunities	0	19 560	82.22	447.00
Population	3	2649	204.99	262.49
• Sweden	0	2219	153.33	191.08
• Other Nordic countries	0	79	3.97	6.05
• Europe (excluding the Nordics)	0	289	9.20	16.27
• Others outside Europe	0	977	38.48	81.87
Income	3	1342	92.96	135.82
• Q1	0	435	22.51	43.27
• Q2	0	252	20.82	32.74
• Q3	0	370	23.82	35.23
• Q4	0	629	25.81	40.02
Car ownership	0.11	0.76	0.41	0.11

provides detailed statistical information for smaller areas within Sweden and remains stable without changing over time. After collecting 372 DeSO zones within the study area, we further divide them into hexagonal grids using H3 system of Uber at resolution 9 (Brodsky, 2018), resulting in each cell having a radius of 178 m and an area of 0.082 km^2. Since these hexagonal zones serve as origins for job accessibility calculations, areas located within water bodies and green spaces were excluded, as these locations do not host residential populations, and their infrastructure development and land use attributes cannot be adjusted through empirical analysis. After this filtering process, a total of 7328 hexagonal grids are retained, with their centroids serving as origin points for the accessibility estimation.

3.2.2. Accessibility-related: grid-level destinations

Grid-level census data is based on the total population register, including the number of formal jobs, and the distribution of individuals by income level and birthplace, sourced from the Swedish Statistics Agency (SCB) (2018-12-31). To ensure privacy, two spatial resolutions are used: 250 × 250 m (small grids) and 1000 × 1000 m (large grids). Large grids are applied in areas with low population density to prevent the identification of residents. While recent data on the locations of informal jobs is unavailable, it is worth noting that these opportunities are typically more accessible and involve shorter commute times and distances than formal jobs (Motte et al., 2016). In total, 3363 job grids are included in the study area, with their centroids serving as destinations for computing job accessibility.

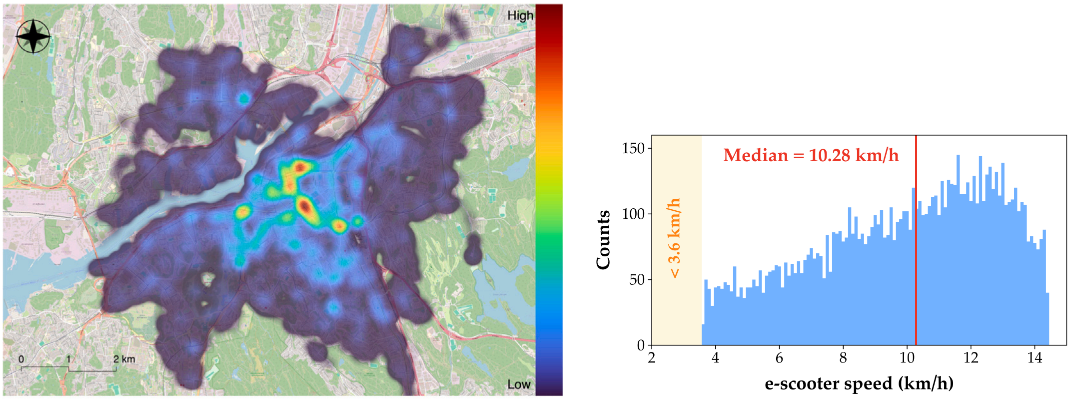
3.2.3. Socioeconomic attributes

Furthermore, population socioeconomic characteristics are also provided in the grid-level census data, including information about birth background, income level, and car ownership. The birth background data document the resident count within each grid categorized by birthplace: Sweden, other Nordic countries, Europe (excluding the Nordics), and other regions outside Europe. Regarding income, each grid records the population falling into four income quartiles in Sweden, where Q1 represents relatively low income, and Q4 represents high income, while Q2 and Q3 are grouped into moderate income levels in this study. The segregation of socioeconomic attributes will be detailed in Section 4.4. Car ownership refers to the number of cars per capita in each grid. The descriptive statistics of census attributes for each grid are summarized in Table 1. We itemized the subcategories under the population and income categories for clarity. The total population within each grid equals the sum of its four subcategories (Sweden, other Nordic countries, Europe excluding the Nordic, and others outside Europe), and the same applies to income.

3.2.4. ESS transaction data

ESS (including VOI and TIER) usage data in the Gothenburg area in 2022 were obtained from an open-source Application Program Interface (API). Each transaction record comprises the e-scooter ID, the geographical coordinates of origins and destinations, battery status, trip distance, and duration. The dataset contains a total of 910,281 ESS usage records. To ensure the analysis focused on regular ESS usage while excluding anomalous cases (e.g., children playing with e-scooters), we removed trips with an average speed below the assumed walking speed of 3.6 km/h (Pereira et al., 2024). This filtering process excluded 94,889 records, leaving 815,392 records as representative of routine ESS usage.

The retained ESS usage data were utilized for two main purposes: First, the average speed of routine ESS trips was calculated to provide a representative speed metric for the Gothenburg region. This metric was subsequently employed to assess the accessibility gains of ESS as a first- and last-mile connection to public transit. Second, the origin and destination points of routine ESS trips were aggregated to identify areas within Gothenburg with active ESS usage and those with minimal or no observed ESS activity. It is worth noting that ESS in Gothenburg is dockless, allowing riders to travel to virtually any location. However, e-scooters cannot be returned outside the operational area. Despite this restriction, we observed occasional anomalies, with one or two trips recorded in non-operational areas. To address this, we implemented a threshold-based filtering strategy to define ESS service availability: areas with an annual aggregate of more than five OD points were classified as "ESS-available regions", while those with five or fewer annual OD points were classified as "ESS-unavailable regions". This categorization facilitates the evaluation of employment accessibility gains provided by ESS across different groups.



(a) Density estimation of the ESS activities. (b) Speed distribution of ESS trips.

Fig. 2. The intensity of ESS activities and their speed distribution.

For visualization, Kernel Density Estimation is used to examine the localized spatial distribution patterns of ESS behaviors. This approach helps identify hotspots and visualizes the intensity and distribution of ESS activities by estimating the probability density function and generating a smoothed spatial surface (Chen and Ye, 2021). As shown in Fig. 2, ESS activities are primarily concentrated in the inner city of Gothenburg, particularly near the Central Station and the vibrant entertainment venue of Valand, which exhibit the highest density. Additionally, the speed distribution of ESS trips exhibits a left-skewed trend, with a median speed of approximately 10.28 km/h.

3.2.5. *GTFS from the public transit system*

Public transport system data is provided in a General Transit Feed Specification (GTFS) format by Trafiklab, an open platform managed by Samtrafiken on behalf of Swedish regional public transport authorities in 2023. This standardized format contains comprehensive public transit information, including transit routes, service schedules, frequencies, stop times, and geographic coordinates of stop locations. The availability of such detailed transit information helps evaluate the accessibility of the current public transit system and its potential integration with other micro-mobility modes such as ESS.

The public transport system analyzed in this study operates under a zone-based ticketing structure. Travelers can choose from single tickets (valid for 90 min), day passes (1, 3, or 7 days), or long-term options like monthly or season passes, all offering unlimited transfers (between buses, trams, trains, etc.) within the validity period and zones (A, B, C). Tickets can be bought through mobile apps, ticket machines, recharge cards, or at designated stores, with discounts available for students, seniors, and children under 7 with a paying adult.

However, ESS services, which are operated by private companies, are not integrated within the current public transit ticketing systems. ESS users are charged independently by multiple operators, each with a slightly different pricing structure. In general, the ESS system operates on a pay-per-ride or subscription model. For the pay-per-ride approach, users have to pay a fixed unlocking fee (around 10 SEK) and a per-minute usage fee (1–3 SEK/minute, depending on the provider). The total cost depends on ride duration. For subscriptions, users can buy daily, weekly, or monthly passes (around 39, 179, 599 SEK, respectively) for unlimited rides within a time limit per ride (e.g., up to 45 min per ride). All payments are processed directly through their mobile apps using various methods, such as credit/debit cards. Operators often provide discounts and promotional codes to attract users.

3.2.6. *Built environment factors*

To investigate the influence of built environment attributes on the accessibility gain brought by ESS, we extracted points of interest (POIs) data from the latest OpenStreetMap (OSM).[2] OSM operates as an open geographic information platform, providing freely accessible geospatial data under the Open Database License. It contains an extensive repository of POI data, covering diverse categories such as public transportation facilities, commercial establishments, recreational areas, and healthcare services. The collaborative nature of OSM ensures that its data is frequently updated by contributors worldwide. This crowdsourced approach enhances the accuracy and reliability of POI data, making it a robust resource for geospatial analyses. It is acknowledged that the quality of labels in OSM exhibits spatial variability. Urban areas tend to feature more comprehensive and well-labeled data due to higher levels of user engagement, while rural areas may suffer from data gaps or inconsistencies. These spatial variations in data quality could potentially affect the accuracy of analysis results, particularly in regions with limited data coverage. Nevertheless, OSM remains a comprehensive and robust tool, widely applied in numerous studies related to transport and built environment (Zhang et al., 2024; Zhou et al., 2023). For ease of accessibility calculation, these POI attributes can be broadly categorized into three

[2] https://www.openstreetmap.org/.

Table 2
The description of built environment attributes.

Built environment factors	Definitions	Unit
Diversity		
Residential land use ratio	Land use ratio of residential POIs in each zone (apartments, etc.)	%
Commercial land use ratio	Land use ratio of commercial POIs in each zone (malls, etc.)	%
Recreational land use ratio	Land use ratio of recreational POIs in each zone (theatre, etc.)	%
Educational land use ratio	Land use ratio of educational POIs in each zone (schools, etc.)	%
Public land use ratio	Land use ratio of public POIs in each zone (banks, etc.)	%
Health land use ratio	Land use ratio of medical POIs in each zone (hospitals, etc.)	%
Other land use ratio	Land use ratio of other POIs in each zone (bridges, etc.)	%
Land use entropy	The land use entropy is an indicator for measuring the degree of land use mix. It is calculated by $K\sum_{i=1}^{N} R_i \ln\left(R_i\right) - \frac{1}{R_i}\ln(K) = 1$, where R_i is the ratio of land use type i and K is the total number of all land use types (Zhang and Zhao, 2017)	%
Road density		
Primary road density	Length of primary roads in each zone divided by the area	km/km^2
Secondary road density	Length of secondary roads in each zone divided by the area	km/km^2
Tertiary road density	Length of tertiary roads in each zone divided by the area	km/km^2
Cycleway road density	Length of cycleway roads in each zone divided by the area	km/km^2
Pedestrian road density	Length of pedestrian roads in each zone divided by the area	km/km^2
Distance to transit		
Station density	Number of public transit stations divided by the area	/km^2
Enabling infrastructure ratio	Land use ratio of ESS enabling infrastructure (crossings, etc.)	%
Hindering infrastructure ratio	Land use ratio of ESS hindering infrastructure (signals, etc.)	%
Other infrastructure ratio	Land use ratio of other infrastructure (speed camera, etc.)	%

dimensions: diversity, road density, and distance to transit. A full list of POI categories is listed in Appendix and their summarization is listed in Table 2.

1. Diversity represents the POI mixture and land use ratios of each analysis zone. Considering the local context in Sweden, we further reclassify the POI data into seven land use categories: residential, commercial, recreational, educational, public, medical, and other. Subsequently, we employ the Term Frequency–Inverse Document Frequency (TF–IDF) technique to quantify the land use ratios within each analysis zone. TF–IDF is a widely used method adapted from the text mining field, which accounts for the imbalance issue in POI categories (Gao et al., 2021; Zhang et al., 2024).
2. Road density pertains to the density of different road types: primary, secondary, tertiary, cycleway, and pedestrian.
3. Distance to transit reflects the coverage and accessibility of transport infrastructure. For transport facilities, we classify POIs into three main categories: enabling, hindering, and others. Enabling facilities motivate the use of ESS (e.g., crossings) while hindering facilities represent scenarios that discourage ESS usage (e.g., traffic signals). Additionally, we incorporate the density of public transit stations, defined as the number of stations within each analysis zone divided by the area.

4. Method

The methodological framework of this study, as illustrated in Fig. 3, has three components. Firstly, to examine how ESS impact job accessibility both as an independent transport mode and when used in integration with public transport (PT), we use processed data to calculate job accessibility across three transport modes: PT, ESS, and integration of PT and ESS. Secondly, we incorporate POI data to characterize land use attributes in each analysis zone and construct explainable machine learning models to interpret the influence of the built environment on the accessibility gains provided by ESS. Finally, we compared the distribution of accessibility gains across different socioeconomic groups to investigate whether the current availability of ESS areas exhibits a bias in positively impacting certain groups over others.

4.1. Accessibility estimation

The employment accessibility defined in this study refers to the cumulative job opportunities reachable within a 30-min travel time from a specific analysis zone, with the origins and destinations respectively approximated as the centroids of hexagonal zones and square grids. The reason for selecting cumulative opportunities as the metric is its ease of communication, operation, and interpretation (Geurs and Van Wee, 2004). Assuming there are P paths from origin zone i to destination grid j, the employment accessibility of zone i can be calculated as:

$$A_i = \sum_{j=1}^{J} D_j \times \max_{p\in P}\left\{I\left(t_{ijp}\right)\right\}, \tag{1}$$

where A_i represents the accessibility of zone i, J is the total number of destination grids, D_j denotes the number of jobs available in grid j, $I\left(t_{ijp}\right)$ is an indicator function that returns 1 if the travel time t_{ijp} is no more than 30 min, and 0 otherwise.

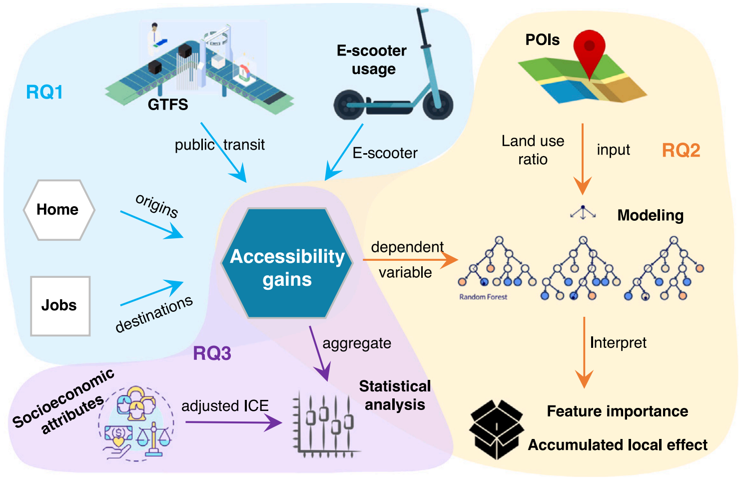


Fig. 3. The methodological framework.

In this study, we followed the routing engine proposed by Conway and Stewart (2019) and implemented it using the r5r package in R (Pereira et al., 2021). We assumed a walking speed of 3.6 km/h, a 30-min threshold for walking (or with ESS) duration to access or egress PT stops, and a maximum of 4 PT legs per trip. The speed of ESS is determined as the median value observed from real usage records within the Gothenburg area, which is around 10.28 km/h, as indicated in Fig. 2. Based on the processed data, there are 7328 origins and 3363 job destinations in total.

In our calculations, we considered the number of job opportunities accessible within a 30-min travel time from each origin point, departing every minute from 2 pm to 3 pm (60-min time window). It is worth noting that the level of public transit service may vary across time periods, potentially introducing uncertainties in accessibility estimates. Fortunately, r5r addresses this by considering multiple departure times (every minute) within the user-specified time window and generating multiple accessibility estimates. As a result, instead of a single value, a distribution of estimates is produced, accounting for the uncertainties in accessibility within the specified time window. To simplify interpretation, one can use the *percentiles* parameter to specify the interested percentiles of the distribution. This study selected the median travel time within the 60-min time window for accessibility estimation, as it has been demonstrated to help mitigate the impact of statistical noise caused by variations in transit services (Conway et al., 2018).

Given the public transit schedule (provided in GTFS), the travel time estimated by r5r in Eq. (1) represents the total duration of a door-to-door journey. It includes the time from the origin to the PT stop, waiting and transfer time at PT stops, time spent onboard, and the time from the alighting stop to the destination (Pereira et al., 2021). ESS can function as first- and last-mile feeders, replacing walking as a connection to public transit and thereby enhancing overall accessibility. However, compared to walking, ESS users incur additional overhead time, which includes locating a nearby available e-scooter, picking it up, and returning it at the destination. For simplicity, this study assumes a fixed overhead time of 3 min. This assumption results in reduced accessibility for ESS-related travel modes, as this overhead period does not contribute to actual travel distance. While this time may vary among individual users, it does not significantly affect the overall spatial distribution of ESS-enabled accessibility from a broader perspective.

4.2. Modeling and analyzing the effects of built environment

After analyzing accessibility gains facilitated by ESS, we employed an interpretable machine learning approach to investigate its potential association with various built environment factors listed in Table 2. One notable advantage of machine learning models lies in their data-driven nature, enabling them to effectively model intricate nonlinear relationships between the dependent variable (i.e., ESS-enabled accessibility gains) and the explanatory variables (i.e., the built environment factors) without requiring explicit specification of the functional form Li et al. (2024) and Cheng et al. (2020).

Extreme Gradient Boosting (XGBoost) was employed as the primary analytical tool in this study due to its exceptional ability to capture intricate relationships, which are essential for understanding ESS-enabled accessibility. XGBoost is a gradient boosting framework that ensembles decision trees to iteratively minimize model errors using a gradient descent optimization process (Chen and Guestrin, 2016). Its parallel computing mechanism ensures scalability for processing large-scale datasets, while preventing overfitting through built-in regularization techniques. Prior research has consistently demonstrated that XGBoost outperforms many alternative machine learning models in terms of both accuracy and computational efficiency (Li, 2023; Zhang et al., 2024; Hu et al., 2021).

In addition, this study introduced two additional ensemble learning approaches, random forest and AdaBoost (Adaptive Boosting), for performance comparison. Random forest aggregates multiple individual decision trees using the bootstrapping method and derives the final response through majority voting (Breiman, 2001). This approach reduces variance by combining the results of numerous weak learners (Cheng et al., 2020). AdaBoost, in contrast, is a sequential ensemble learning method that trains weak learners, typically shallow decision trees, while iteratively adjusting weights to focus on more challenging cases (samples with larger prediction errors) (Freund and Schapire, 1997). Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared were employed as performance metrics to evaluate the predictive accuracy of these models.

During model construction, the dataset was randomly partitioned, with 70% allocated for training and the remaining 30% reserved for testing. A five-fold cross-validation strategy was applied to the training set to evaluate the predictive capability of different parameter combinations and to identify the optimal configuration using grid search. For XGBoost, five key hyper-parameters were considered: the number of decision trees, maximum tree depth, boosting learning rate, minimum sum of instance weight needed in a child node, and subsample ratio. For random forest, we focused on the number of decision trees, maximum tree depth, and the minimum number of samples required to split an internal node. For Adaboost, we focused on tuning the number of base decision trees, the learning rate, and the maximum depth of each single tree. The model with the highest R-squared was ultimately selected for interpretation.

4.3. Model-agnostic interpretation approach

We leveraged the accumulated local effect (ALE) approach to reveal the nuanced relationship between the ESS-enabled accessibility gains and crucial built environment attributes. ALE is a data-driven and model-agnostic technique that interprets how features impact predictive machine learning models on average (Apley and Zhu, 2020; Molnar, 2020). Notably, ALE utilizes the conditional distribution to average over other features. Instead of averaging the predictions directly, it averages the differences in predictions, thereby mitigating the influence of correlated features (Sun et al., 2024; Gao et al., 2023). This constitutes a significant advantage of ALE over partial dependence plots, which assume no correlation among features. The function of ALE in one dimension can be described as:

$$\begin{aligned} \mathrm{ALE}\left(x_s\right) &= \int_{\min(x_s)}^{x_s} \mathbb{E}\left[\frac{\partial f\left(x_s, x_R\right)}{\partial x_s} \middle| \, x_s = z_s \right] d\left(z_s\right) - c_s \\ &= \int_{\min(x_s)}^{x_s} \int \mathrm{P}\left(x_R \mid z_s\right) \frac{\partial f\left(z_s, x_R\right)}{\partial z_s} d\left(x_R\right) d\left(z_s\right) - c_s, \end{aligned} \tag{2}$$

where $\frac{\partial f(x_s, x_R)}{\partial x_s}$ characterizes the local effect of the specific feature x_s on the predictive outcome (i.e., accessibility gains). This gradient can be approximated using the first-order difference if the model function $f(\cdot)$ does not provide gradients. x_R represents the remaining complementary features used in the model fitting, and c_s denotes a constant term introduced to centralize ALE.

Additionally, we incorporated SHAP (SHapley Additive exPlanations) as a complementary interpretability tool. Grounded in game theory principles, SHAP offers a comprehensive framework for both global and local (instance-level) explanations of model behavior (Lundberg and Lee, 2017). It quantifies feature contributions by computing SHAP values, which represent the marginal impact of each feature on individual predictions, ensuring fair and consistent attribution across all features. Mathematically, the SHAP value ϕ_j for feature j is given by:

$$\phi_j = \sum_{S \subseteq \{1,\ldots,p\} \setminus \{j\}} \frac{|S|!(p-|S|-1)!}{p!} \left[f\left(\mathbf{x}_{S\cup\{j\}}\right) - f\left(\mathbf{x}_S\right) \right], \tag{3}$$

where p is the set of all features, S is a subset of p excluding j, $|S|$ is the size of S, $f\left(\mathbf{x}_S\right)$ represents the model outcome with features in S, and $f\left(\mathbf{x}_{S\cup\{j\}}\right)$ is the prediction when feature j is added.

The absolute SHAP value can quantify the importance of a given feature to a local prediction by measuring the magnitude of its contribution to the model output, regardless of its direction (positive or negative) (Molnar, 2020). Compared to ALE, SHAP offers superior capabilities in interpreting individual predictions, handling feature interactions, and offering more granular insights, albeit at a higher computational cost. Fortunately, Lundberg et al. (2020) developed the Tree SHAP algorithm, which computes SHAP values in polynomial time and is specifically optimized for tree-based ensemble models. As a result, this study employed Tree SHAP to efficiently compute SHAP values, providing insights into the associations between built environment attributes and ESS-enabled accessibility gains.

4.4. Socioeconomic disparities in accessibility gain

To investigate differentiation in accessibility gains from ESS across socioeconomic attributes, we quantify how spatially separated populations reside in the study area, i.e., residential segregation (Feitosa et al., 2007). We consider populations of birth backgrounds, that is, native-born and foreign-born outside Europe, and income, i.e., the lowest and the highest quantile groups. We first unify the spatial analysis units. Since square grids containing socioeconomic attribute information are slightly larger than hexagonal zones and are challenging to subdivide, we adopt a weighted approach to aggregate the hexagon-based accessibility gains into square grids. This weighting method involves multiplying the proportion of the hexagonal area covered by each square grid by their original accessibility gains. For example, if a square grid covers three hexagonal zones (denoted as Q, M, N) and the areas intersecting with them are q, m, and n, respectively, then the aggregated accessibility gain for this grid would be calculated as

$$A = \frac{q}{Q} \times A_Q + \frac{m}{M} \times A_M + \frac{n}{N} \times A_N. \tag{4}$$

To quantify residential segregation, we introduce the adjusted Index of Concentration at the Extremes (ICE) to measure whether a grid is segregated towards a certain group (Liao et al., 2024b,a). The ICE is a statistical indicator to describe the extent to which the population in a specific area is concentrated by characteristics that are either advantageous or disadvantageous, given the socio-demographic composition of the region (Massey, 2001). It is particularly useful for analyzing disparities in income distribution and has been successfully applied in other fields like public health (Krieger et al., 2016). This approach provides a more nuanced measure of inequality than traditional measures, as it specifically focuses on the extremes of the distribution rather than the entire distribution.

The adjusted ICE can be calculated using Eq. (5) for a given zone j. This indicator measures the deviation of areas from the national average composition of birth background and income. By placing local segregation patterns in a national context, it aids in informed decision-making and policy development.

$$ICE_j = \frac{\frac{A_j}{w_A} - \frac{B_j}{w_B}}{\frac{A_j}{w_A} + \frac{B_j}{w_B} + \frac{O_j}{w_O}}, \tag{5}$$

where A_j is the number of foreign-born (outside Europe) individuals or the ones in the highest income quantile group, B_j the number of native-born individuals or the ones in the lowest income quantile group, and O_j the remaining individuals. The overall fraction of A, B, and other populations at the national level are w_A, w_B, and w_O, respectively, which are non-zero values. We use the data from 2019, where birth background segregation (ICE_{jb}) applies the shares of 80.44% native-born and 11.07% foreign-born (outside Europe). Moreover, income segregation (ICE_{ji}) applies the shares of 25% for low-income and high-income groups. The outcome of ICE calculation is a value ranging from −1 to 1, where −1 signifies complete segregation towards foreign-born or low income, and 1 indicates complete segregation towards native-born or high income.

We developed a randomization simulation to establish thresholds for identifying segregated areas. This simulation creates a scenario, Random mixing, where individuals in Sweden make random housing choices, leading to a diverse mix of groups by birth background and income level. In this process, we randomly reassign residences among individuals and then assess the level of residential segregation for each area. After completing this randomization process 100 times, we compile and analyze the distribution of residential segregation levels for the study area. Residential segregation values outside the confidence interval 99% are deemed statistically segregated. Consequently, areas with birth background segregation levels between −0.2 and 0.2 are considered insignificantly segregated. Similarly, areas with income segregation levels greater than 0.3 or less than −0.3 are considered significantly segregated. After this step, we have three groups of regions for birth background, Foreign-born (outside EU) segregated ($ICE_{jb} < -0.2$), Mixed ($-0.2 \leq ICE_{jb} \leq 0.2$), and Native-born segregated ($ICE_{jb} > 0.2$), and three groups of regions for income level, Low income ($ICE_{ji} < -0.3$), Moderate ($-0.3 \leq ICE_{ji} \leq 0.3$), and High income ($ICE_{ji} > 0.3$).

5. Results

In this section, we first describe the statistical results of the built environment variables and visualize the distribution of socioeconomic attributes based on ICE segregation, providing an overall understanding of the study area. Next, we present the employment accessibility results under the scenarios of using three different transport modes (i.e., PT, ESS and integration of PT and ESS) and quantify the accessibility gains brought by ESS. Following this, we present the results of the random forest and how to interpret the influence of built environment factors on accessibility outcomes. Finally, Section 5.4 explores whether the current ESS accessible areas exhibit any bias towards different socioeconomic groups and assesses whether they adequately address the needs of those reliant on public transport for daily commuting. The code and related data are publicly available at https://github.com/LiyangHu97/ESS-accessibility.

5.1. Descriptive analysis

The descriptive statistics for all explanatory variables and accessibility are summarized in Table 3. Fig. 4 presents the spatial distribution of ICE segregation-based socioeconomic attributes, car ownership, and jobs. As depicted in Fig. 4(a), the foreign-born (outside EU) population is concentrated in three distinct clusters located in the northeastern (further north), northern, and southwestern corners of study area. These clusters are also associated with relatively lower income levels (see Fig. 4(b)), lower car ownership (see Fig. 4(c)), and fewer job opportunities (see Fig. 4(d). Consequently, residents in these demographic regions rely more on public transit for their daily commutes.

On the contrary, most downtown areas feature a composition of native- and foreign-born residents, indicating non-segregation by ICE calculation results. These regions also demonstrate relatively high-income levels, ranging from moderate to high-income brackets, as shown in Fig. 4(b). However, it is noteworthy that due to their close proximity to the central business district, where the majority of jobs are concentrated, and their favorable accessibility to public facilities, there exists a low prevalence of car ownership among the population in these areas. They can reach such neighborhoods with a short walk or ride.

The areas segregated towards native-born populations are primarily distributed around the periphery of Gothenburg, characterized by relatively elevated income levels. Unlike the affluent cohorts in the city center, these outlying native-born communities generally hold a higher car ownership. This trend is likely attributed to their considerable distance from employment hubs like the central areas and limited availability of public transit infrastructure. In consequence, they rely heavily on private vehicles for commuting purposes.

Table 3
Descriptive statistics of all variables.

Variables	Min	Max	Mean	STD
Accessibility	0.00	84 451.00	7914.45	16 355.80
Diversity				
Land use entropy	0.00	1.16	0.24	0.31
Residential land use ratio	0.00	1.00	0.11	0.23
Commercial land use ratio	0.00	1.00	0.06	0.17
Educational land use ratio	0.00	1.00	0.02	0.09
Recreational land use ratio	0.00	1.00	0.11	0.23
Public land use ratio	0.00	1.00	0.04	0.13
Health land use ratio	0.00	0.81	0.00	0.04
Other land use ratio	0.00	1.00	0.36	0.41
Road density				
Primary road density	0.00	24.04	0.49	1.83
Secondary road density	0.00	30.23	0.47	1.85
Tertiary road density	0.00	67.48	6.20	7.41
Cycleway road density	0.00	30.24	2.20	3.37
Pedestrian road density	0.00	72.70	7.04	7.47
Distance to Transit				
Enabling infrastructure ratio	0.00	1.00	0.17	0.32
Hindering infrastructure ratio	0.00	1.00	0.02	0.12
Other infrastructure ratio	0.00	1.00	0.28	0.41
Station density	0.00	244.61	4.21	12.26

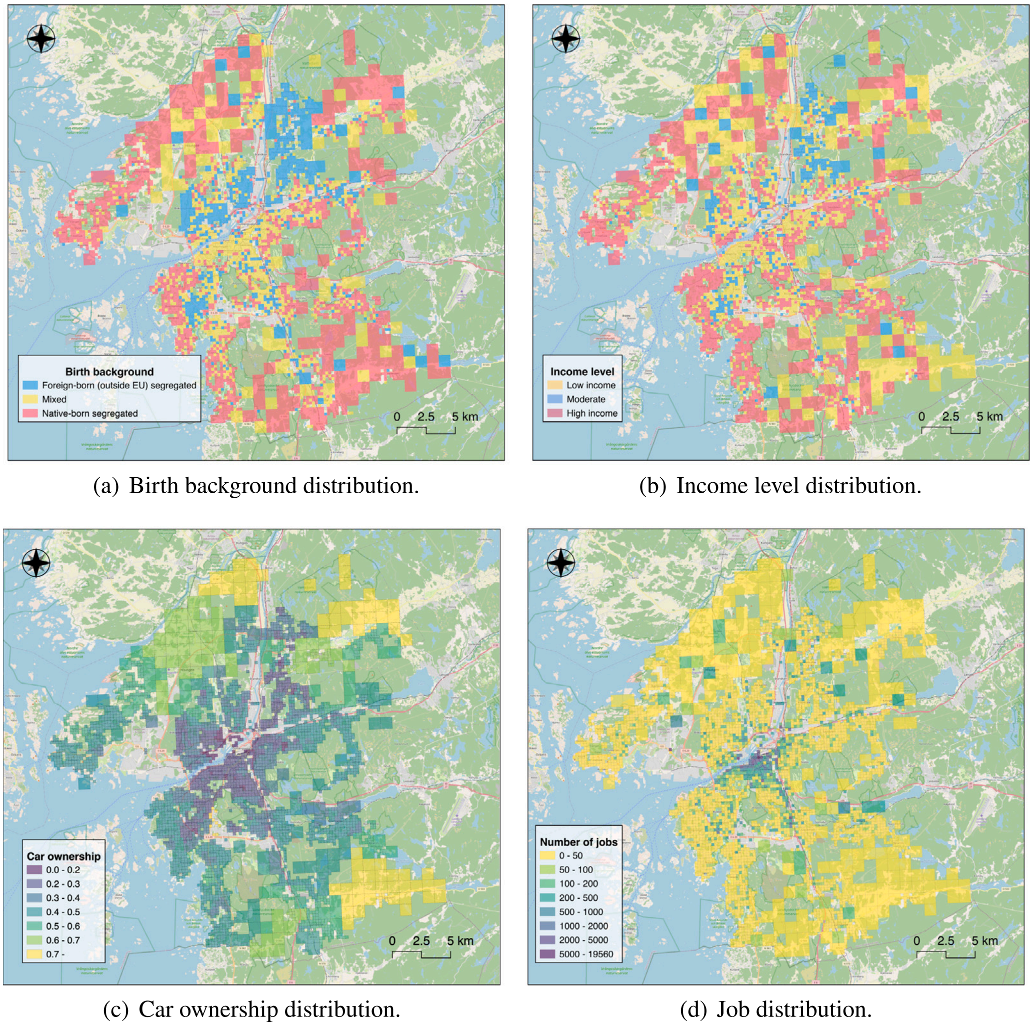
5.2. Spatial distribution of employment accessibility gains

Fig. 5 presents the spatial distribution of employment accessibility within a 30-min travel time for three transport modes: public transit-only, ESS-only, and transit integrated with ESS. This figure provides the spatial context for the analyses in this paper, showing the distribution of accessibility conditions across the city under each transport mode scenario. The combined transport mode uses ESS as a first- and last-mile alternative to walking, connecting with transit to significantly enhance accessibility. All scenarios exhibit a pattern of high accessibility in the central areas, gradually decreasing towards the periphery, with Gothenburg center serving as a focal point that disperses accessibility along transit routes outward. This phenomenon can be explained by the concentration of jobs and the extensive public transit services available in the city center.

Furthermore, Fig. 5 also illustrates the varying levels of accessibility provided by different transport modes. The public transit system offers relatively higher levels of accessibility for corridors from the city center to the periphery. Compared to ESS as a standalone mode, public transit better serves populations in the outer urban areas. In contrast, ESS as a standalone mode primarily cater to urban core residents and align with their predominant usage in these areas (refer to Fig. 2), with limited convenience provided to residents in the outskirts. On the other hand, ESS can expand the PT system's reach beyond the vicinity of PT stations when employed as an on-demand feeder service.

To examine the benefits of integrating ESS as a first- and last-mile feeder with public transit and how such benefits manifest spatially, we delineated the accessibility gains facilitated by ESS, as shown in Fig. 6(a). It describes the number of jobs reachable within a 30-min from different areas of Gothenburg when using ESS in conjunction with public transit, in contrast to relying solely on public transit. We also conducted a hot spot analysis of the accessibility gains using the Getis–Ord Gi* statistic (Getis and Ord, 1992). This approach identifies whether areas with accessibility gains are statistically significant based on neighboring features. The results are displayed in Fig. 6(b), where approximately 15% of the study areas experience a significant enhancement in job accessibility with at least a 90% confidence level.

Overall, the accessibility gains from using ESS as a first- and last-mile connection to public transit are well distributed throughout the city of Gothenburg and its surrounding towns. As expected, the absolute value of accessibility gains is most pronounced in the main urban areas. This observation is likely attributable to the higher accessibility levels prevalent in these central areas, where commuting needs can be effectively addressed by public transit systems, such as trams, even without the utilization of ESS. Most of these areas exhibit statistical significance at a 99% confidence level and benefit both wealthy and less wealthy residents. Meanwhile, suburban areas along public transit corridors, such as Kortedala, Hjällbo, and Hammarkullen in the northeast, as well as Västra Frölunda in the southwest, also witness notable accessibility gains. These localities are primarily inhabited by a substantial population of foreign-born residents with relatively lower income levels and lower car ownership. Similar phenomena can also be observed in some areas in the southern part of Gothenburg, such as Mölndal. Consequently, transport planning and policy-making should place greater emphasis on these groups that rely heavily on public transit. A detailed discussion and quantitative comparison of job accessibility equity among different socioeconomic groups can be found in Section 5.4.



(a) Birth background distribution.

(b) Income level distribution.

(c) Car ownership distribution.

(d) Job distribution.

Fig. 4. Spatial distribution of socioeconomic attributes and job opportunities.

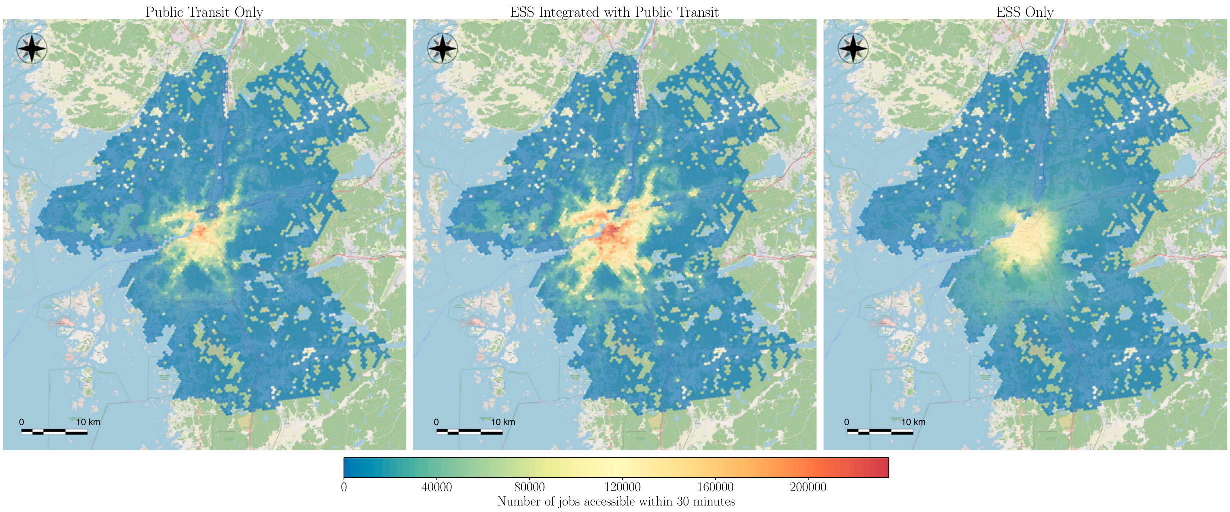
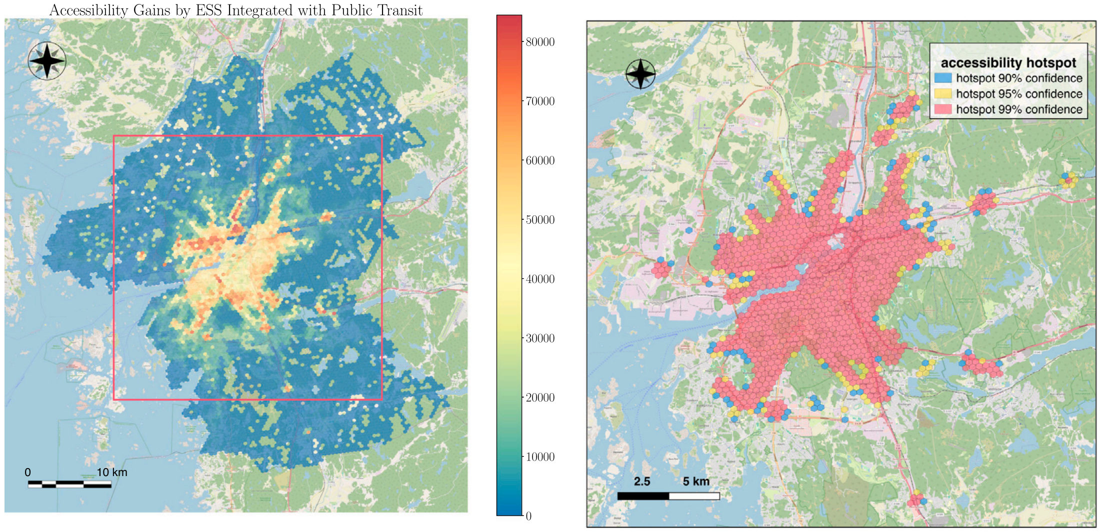


Fig. 5. Spatial distribution of employment accessibility by different transport mode alternatives.



(a) Accessibility gains by ESS.   (b) Hot spot areas for accessibility gains.

Fig. 6. Accessibility gains and significantly benefited areas attributed to the integration of ESS.

Table 4
Performance of different machine learning models.

	XGBoost		Random forest		Adaboost	
	Training	Testing	Training	Testing	Training	Testing
RMSE	9551.43	10 735.57	9491.47	10 970.59	9298.67	11 034.51
MAE	5033.98	5672.45	5123.80	5858.36	5451.21	6253.33
R-squared	0.66	0.58	0.66	0.56	0.67	0.55

5.3. Influence of built environment attributes on ESS-enabled accessibility gains

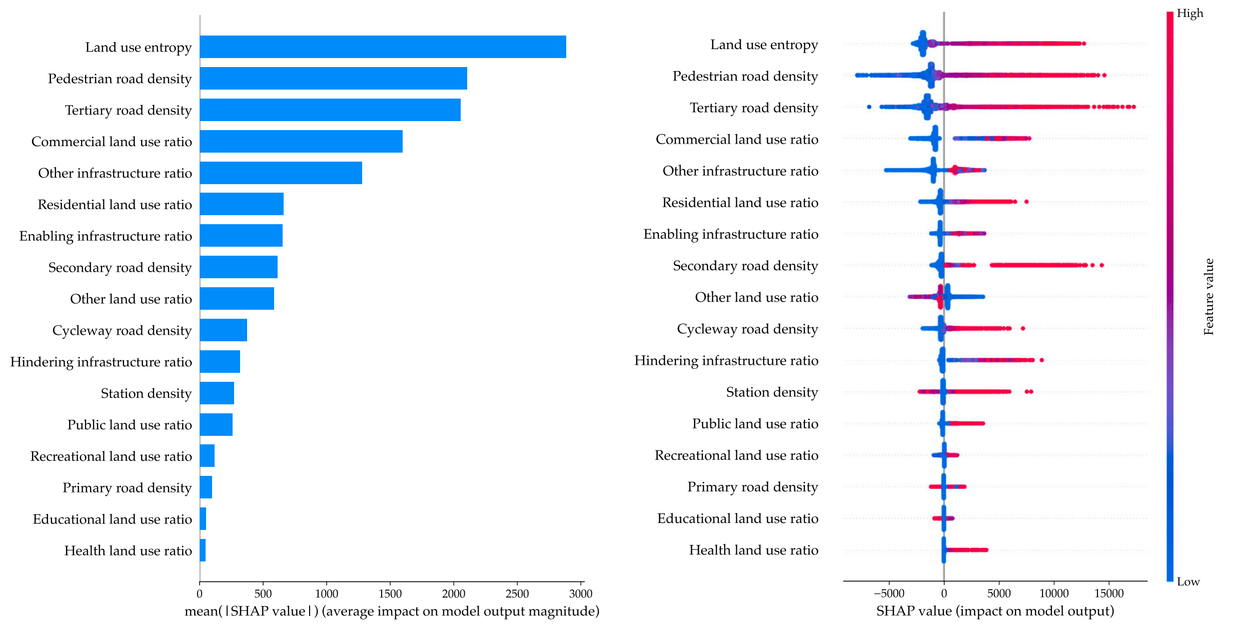
5.3.1. Model performance assessment

The performance of the best configurations of three machine learning approaches are summarized in Table 4. Overall, their R-squared values on the testing set are comparable, with XGBoost slightly outperforming others at 0.58. This advantage is likely attributable to the unique ensemble mechanism of XGBoost, particularly its incorporation of second-order derivatives during the optimization process. The similarity in R-squared values across different models suggests that the selected built environment factors collectively explain approximately 56% (averaged across the three models) of the accessibility gains introduced by ESS. Considering the spatial heterogeneity across regions, an explanatory power of 56% is highly satisfactory. While this accuracy could potentially be enhanced by incorporating geographically weighted models that account for spatial heterogeneity, such approaches essentially involve modeling each region individually, sacrificing the ability to provide a global interpretation—a crucial feature for urban planners and practitioners.

5.3.2. Model interpretations

Based on the optimal XGBoost model, we computed and visualized SHAP values in Fig. 7. Fig. 7(a) presents SHAP-based global feature importance, where land use mix (measured by entropy) demonstrates the highest importance, followed by road density characteristics such as pedestrian and tertiary road density. This observation may reflect the close relationship between road network density and urban mobility within these locales, though other unobserved spatial factors may also contribute to these relationships. In addition, the results indicate a strong correlation between the ratios of commercial and residential land use and accessibility gains. This is likely due to the more extensive road infrastructure surrounding commercial and residential areas, which enhances accessibility gains achieved by using ESS as an alternative to walking and PT connections. Conversely, land use types with potentially less developed road infrastructures, such as educational and health-related areas, demonstrate relatively weaker associations with accessibility gains enabled by ESS.

To further examine these relationships, we created scatter plots of SHAP values in Fig. 7(b), where each point represents a SHAP value for a feature and a specific instance. Overall, most built environment attributes demonstrate a positive relationship with ESS-enabled accessibility gains; for example, higher land use mix and greater pedestrian road density typically correspond to larger accessibility gains. Considering that ALE provides detailed insights into feature effects on model outputs while accounting for feature correlations, we generated ALE plots for the four most significant built environment attributes within each category,



(a) SHAP-based global feature importance. (b) Scatter plots of SHAP values ordered by feature importance.

Fig. 7. Summary of SHAP-based global feature importance.

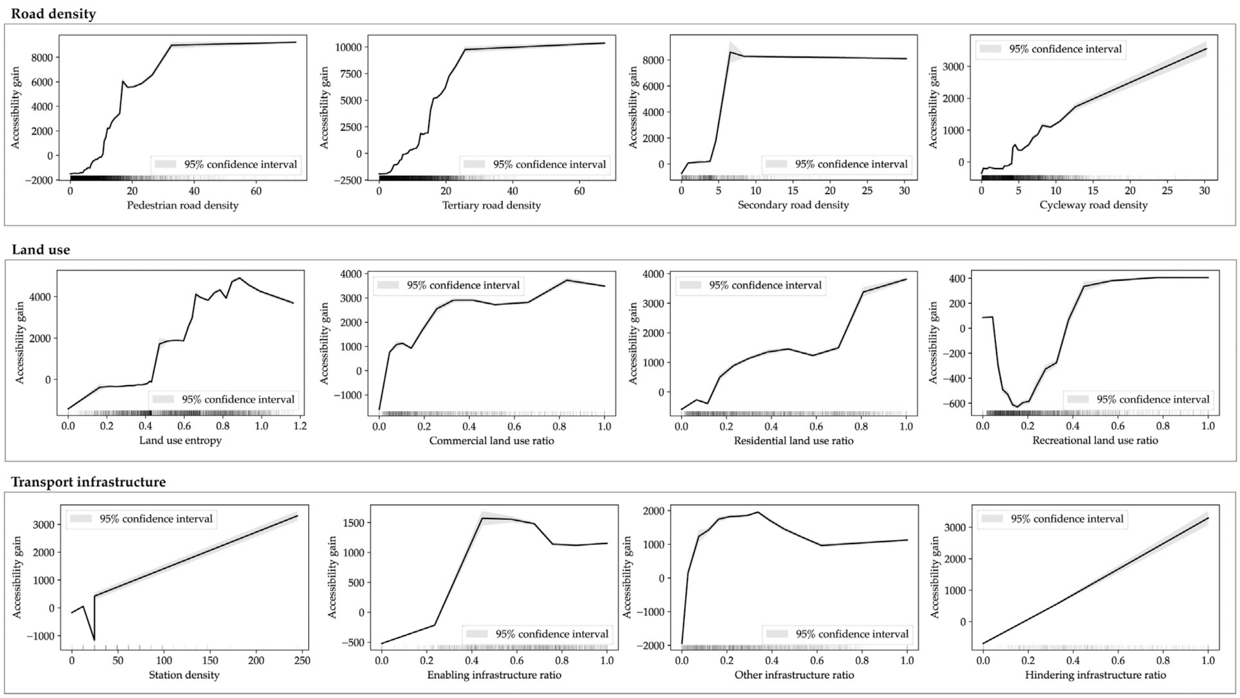


Fig. 8. ALE effects of the four most important built environment attributes under each category.

with the results presented in Fig. 8. In each subplot, the x-axis represents the data distribution. ALE estimates are more robust and reliable in regions with dense data distribution but become less reliable and more prone to noise in sparser regions.

Overall, most built environment factors exhibit positive and nonlinear associations with ESS-enabled accessibility gains, although some factors demonstrate linear relationships within certain ranges. This observation aligns with our previous analysis from Fig. 7(b). Generally, areas with higher road density correspond to greater route options for residents, which enhance connectivity and correlate with increased accessibility gains when ESS is considered as an alternative to walking and public transit connections. High-density road networks may facilitate the coexistence of various micro-mobility systems, such as ESS, shared bicycles, and public transit, potentially enhancing accessibility gains where these systems are effectively integrated. However, empirical evidence from Fig. 8 indicates that these relationships are not uniformly positive but demonstrate threshold effects. For example, the relationship between accessibility gains and pedestrian road density levels off at approximately 33 km/km^2, while for tertiary roads, this occurs around 28 km/km^2. Beyond these thresholds, additional road density does not correspond to significant increases in ESS-enabled accessibility gains. Similarly, the associations between secondary road density and accessibility remain positive but become more gradual above 8 km/km^2. These empirical observations suggest that beyond certain density thresholds, the potential for additional accessibility gains from road network characteristics may diminish.

Regarding land use attributes, areas with higher entropy values — representing more diverse land use attributes — are positively associated with ESS-enabled accessibility gains. This suggests that diverse land use attributes may enhance the accessibility benefits brought by ESS. Other land use attributes exhibit segmented relationships with ESS-enabled accessibility gains. Specifically, the relationship between the commercial land use ratio and accessibility gains is more pronounced within the 0–0.4 range but gradually flattens out thereafter. In contrast, the residential land use ratio shows an opposite trend, with a modest association in the 0–0.6 range that becomes stronger beyond 0.6. This pattern may reflect the fact that higher residential ratios are often associated with larger populations, which can correspond to the development of more extensive public transit infrastructure. Similarly, the recreational land use ratio demonstrates a stronger relationship with accessibility gains within the 0.2–0.4 range, consistent with broader trends observed in our analysis.

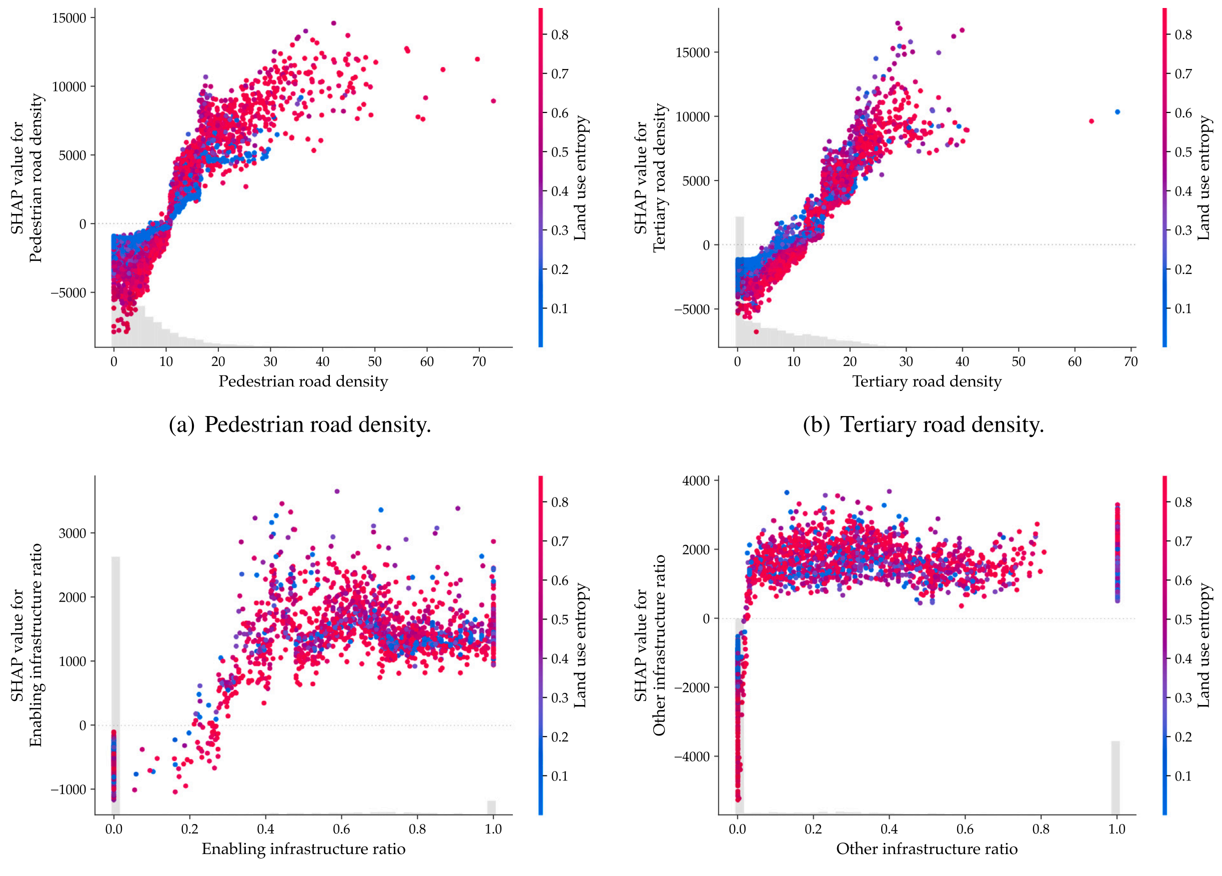
The association between PT station density and ESS-enabled accessibility gains shows a nearly linear pattern when density exceeds 20 stations/km^2. Areas with higher PT station densities are associated with larger increases in accessibility gains when ESS is added in these regions. For ESS-enabling infrastructure, we observe a positive, nearly linear relationship with accessibility gains when the ratio is below 0.4; however, this association becomes negligible beyond this threshold. Infrastructure POIs categorized as "Other infrastructure" (e.g., speed cameras), exhibit a positive association with ESS-enabled accessibility gains for ratios below 0.2. Interestingly, our analysis reveals an unexpected linear relationship between potential accessibility gains and ESS-hindering infrastructure. While we cannot determine causation, we note that traffic signals tend to be more prevalent in urbanized areas (Maparu and Mazumder, 2017), which also typically have higher concentrations of PT stations. This spatial co-occurrence might help explain the observed relationship between the ratio of ESS-hindering infrastructure and the potential accessibility gains resulting from ESS implementation.

Furthermore, we leveraged the advantage of SHAP in capturing marginal relationships and feature interactions by creating SHAP-based dependence plots. The results are presented in Fig. 9, where all subplots were color-coded by land use entropy to illustrate how land use mix interacts with other critical features. Land use entropy was selected as the interaction effect of interest primarily because it is the most important variable and can be analyzed in conjunction with features like road density to understand their mutual interactions and joint contributions to accessibility gains. These insights can provide valuable guidance for urban planning and policy-making. Overall, the relationships between various features and accessibility gains exhibit positive yet nonlinear trends, which align with the findings from the ALE analysis. The interaction between pedestrian road density and land use entropy reveals notable patterns. When pedestrian road density is below 10 km/km^2, higher land use mix tends to correspond to lower accessibility gains. However, this trend reverses when pedestrian road density exceeds 10 km/km^2. A similar phenomenon is observed for tertiary road density, as shown in Fig. 9(b), with a turning point around 15 km/km^2. This relationship likely stems from the complementary roles of road density and land use mix: road density associates with the efficiency of ESS passage, while land use diversity relates to potential connectivity paths. These factors interact synergistically, whereby areas with greater road density and a more diverse mix of land uses tend to achieve higher accessibility gains. Fig. 9(c) illustrates the marginal associations between enabling infrastructure ratio and accessibility gains. When other variables remain constant, enabling infrastructure ratio demonstrates a positive and nonlinear relationship, which aligns with the ALE analysis results from Fig. 8. No discernible interaction effect between land use entropy and enabling infrastructure ratio was observed. While a similar trend appears in the other infrastructure ratio, it differs by exhibiting a noticeable interaction effect with land use entropy. In areas without other infrastructure, more homogeneous land use types may lead to greater accessibility gains. Conversely, in areas dominated by other infrastructure types (other infrastructure ratio = 1), more diverse land use attributes are associated with higher accessibility gains. These instance-level SHAP-based dependence plots not only delineate nonlinear feature effects but also provide granular insights into feature interactions.

5.4. Socioeconomic disparities on accessibility gains

It is noteworthy that ESS are not available in all regions, but are mainly concentrated in the urban centers, as illustrated in Fig. 2. In addition, as shown in Fig. 4(c), there is a population group in the northeast of Gothenburg characterized by low car ownership but limited availability of ESS. Based on these observations, this subsection examines (1) whether there is a bias in the accessibility benefits experienced by different socioeconomic groups in the city center, where ESS is actively used, and (2) what potential accessibility benefits exist for disadvantaged groups reliant on public transit in areas with minimal ESS activity.

As described in Section 3.2.4, we categorized the study area into regions with active and inactive ESS activity by calculating the aggregated annual number of OD trips in each hexagon. For clarity of discussion, we refer to hexagons with annual OD trips greater than five as "ESS-available regions" and those with five or fewer annual OD trips as "ESS-unavailable regions". Within the ESS-unavailable regions, we focused exclusively on those with car ownership rates below 0.25, as most residents with high car ownership in suburban areas are more likely to rely on private cars rather than public transit. The relationship with respect to the birth background and income levels of populations in such two regions is displayed in Fig. 10.

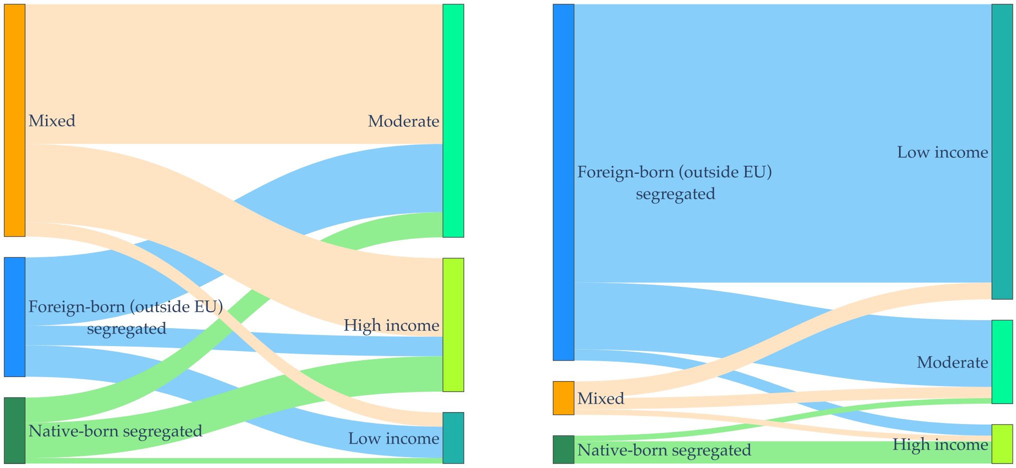


(a) Pedestrian road density. (b) Tertiary road density. (c) Enabling infrastructure ratio. (d) Other infrastructure ratio.

Fig. 9. SHAP-based dependence plots for important attributes. The points on each scatter plot are color-coded based on land use entropy, illustrating the interaction effect between land use entropy and the corresponding feature. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

It can be observed that most of the ESS-available areas are characterized by a mix of foreign-born (outside EU) and native-born people with moderate income levels. Among foreign-born (outside EU) residents, the majority have moderate income levels, whereas native-born individuals tend to have higher incomes. This suggests that ESS availability may cater to a diverse population, but with a focus on those with medium income levels. Conversely, in ESS-unavailable (with minimal ESS activity) areas, a significant proportion (around 85%) of the population consists of foreign-born (outside EU) individuals, primarily from the low-income group (around 70%). Moreover, their car ownership ratio is less than 0.25, indicating a higher reliance on alternative modes of transport such as public transit or walking/biking. These findings highlight the vulnerability of this population group in terms of employment accessibility. Therefore, in future policy and land use planning, more attention should be given to these disadvantaged populations who reside far from CBD and are less wealthy.

Fig. 11 illustrates the percentage increase in accessibility for areas within regions where car ownership is less than 0.25, with black ellipses indicating areas currently lacking ESS availability. It is worth noting that, instead of using absolute values, we employ the percentage increase in accessibility as a relative measure, aiming to quantify how much the employment accessibility within each region can be improved by the introduction of ESS. The calculation involves dividing the accessibility gain of each region by its initial accessibility (i.e., public transit integrated with walking), expressed as a percentage. The results reveal that most regions with low car ownership are covered by ESS services. Areas without ESS availability are primarily located on the outskirts of the city center, particularly in the northeast of Gothenburg. This pattern aligns with the distribution of foreign-born (outside EU) populations as shown in Fig. 4(a) and corroborates the statistical findings presented in Fig. 10(b). However, it is noteworthy that these peripheral areas exhibit higher percentage increase in accessibility compared to the city center. This discrepancy is probably attributed to the differences in baseline accessibility. Gothenburg central serves as an employment hub with abundant job opportunities and extensive public transit facilities, resulting in initially high levels of employment accessibility. In contrast, residents in the outer suburbs have to depend heavily on limited public transit services to commute to the city center. The introduction of ESS in these peripheral areas can achieve significant accessibility improvements by providing an efficient first- and last-mile connection to public transit, thereby substantially enhancing overall accessibility. This analysis underscores the potential of ESS to bridge accessibility gaps in suburban



(a) ESS-available regions. (b) ESS-unavailable regions.

Fig. 10. The relationship between population birth background and income level in two separate groups of regions by the availability of ESS.

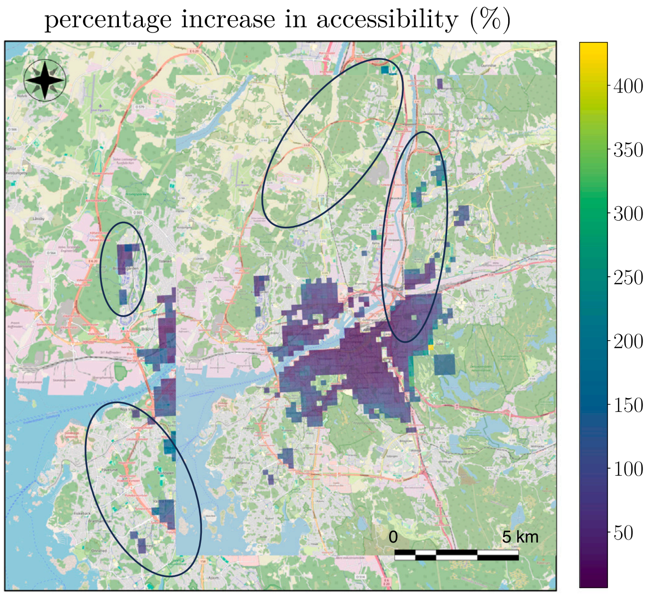


Fig. 11. Percentage increase in accessibility in areas with car ownership less than 0.25 (i.e., areas with residents mainly reliant on public transit). Black ellipses characterize areas where ESS are currently unavailable.

areas with limited public transit options, particularly benefiting disadvantaged populations. Further quantitative comparisons and detailed analyses will be provided subsequently to delve deeper into these findings and their implications for urban mobility and equity.

Fig. 12 presents the percentage increase in accessibility for different birth background groups within two separate regions: areas with and without ESS availability. Each dot in the figure represents an analysis zone, with side plots illustrating the distribution of samples. In regions where ESS are currently available, native-born residents have an average percentage increase of around 80%, while foreign-born (outside EU) segregated and mixed communities enjoy an average percentage increase of approximately 68%. This indicates a 12% higher rate for native-born individuals compared to foreign-born and mixed groups. However, the Mann–Whitney U test reports a p-value of 0.106, suggesting that the difference is not statistically significant. In regions without available ESS, the majority of the population is foreign-born (outside EU). These peripheral areas show significantly higher potential percentage increase in accessibility than the ESS available regions at a confidence level above 99%. Foreign-born individuals could achieve an average percentage increase of approximately 143%, while a small number of native-born individuals could also attain an average percentage increase of 130%. From a job accessibility perspective, this demonstrates the substantial potential benefits of

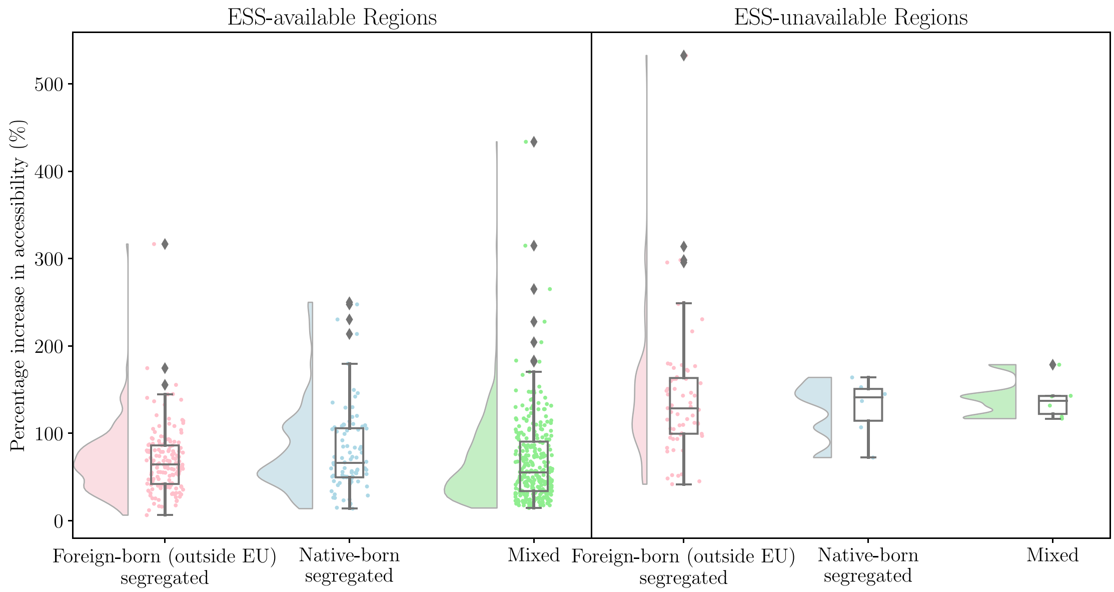


Fig. 12. Distribution comparison of the percentage increase in accessibility for different birth background groups.

introducing ESS in the foreigner-grouped outskirts, which currently lack ESS coverage. The results on the income level are similar to the birth background because most foreign-born (outside EU) segregated regions are also low-income areas (see Fig. 10).

These observations highlight critical equity issues. Although the integration of ESS as a first- and last-mile feeder to public transit can significantly enhance job accessibility, the current ESS services in Gothenburg primarily benefit native-born and high-income groups. However, there are vulnerable populations highly dependent on public transport, particularly in the northeastern part of Gothenburg, who are not adequately served. These individuals are mostly foreign-born (outside EU), low-income, and have low car ownership. Quantitative results suggest that introducing ESS to these under-served areas could yield even more significant benefits than in the city center, with potential accessibility gains of up to 143%. How to design and deploy shared ESS in such under-served areas requires future consideration of economic viability, system efficiency, and feasibility. Ensuring the equity of emerging micro-mobility services, especially for disadvantaged groups, can help bridge accessibility gaps and promote the inclusiveness of urban transport systems.

6. Discussions and conclusion

This study examines how ESS, an emerging micro-mobility transport mode, shape spatial and socioeconomic differences in job accessibility in Gothenburg, serving as a first- and last-mile feeder to public transit. To this end, we integrated official employment data, GTFS data, and extensive real-world ESS usage data to calculate the cumulative job opportunities benefited by replacing walking with ESS in conjunction with public transit within a 30-min travel time, referred to as accessibility gains. Additionally, to decipher the relationship between ESS-enabled accessibility gains and built environment factors, we modeled the POIs extracted from OSM using a machine learning approach and introduced two model-agnostic methods, ALE and SHAP, for interpretation. Lastly, we focused on the equity issue of ESS accessibility by employing an adjusted ICE indicator at a 99% confidence level to assess accessibility benefits across different segregated socioeconomic groups by birth background and income level.

The results indicate that ESS can effectively enhance overall employment accessibility, with cumulative job opportunities showing strong benefits in central areas and diminishing along public transit corridors towards the outskirts. Statistical analysis reveals that approximately 15% of the regions can significantly benefit from ESS integration at a confidence level of at least 90%. However, not all of these areas currently have ESS service. Within the available areas around Gothenburg central, the accessibility gains vary across different socioeconomic groups. For example, native-born groups enjoy an average percentage increase in accessibility of around 80%, which is 12% higher than foreign-born and mixed groups. Conversely, in suburban areas such as the northeastern regions of Kortedala, Hjällbo, and Hammarkullen, where ESS are unavailable, there is a concentration of low-income, foreign-born (outside EU) residents (with approximately 85% foreign-born and 70% low-income individuals). These groups could potentially achieve a 143% accessibility gain from ESS integration, which is significantly higher than that in central areas at a confidence level of above 99%. Besides, it is worth noting that these groups have a car ownership rate of less than 0.25, indicating their reliance on public transit as their primary mode of travel. Therefore, in future transport planning and policy-making, special attention should be directed towards under-served outskirts with concentrated disadvantaged populations, while considering the overall economic viability, efficiency, feasibility, and safety of the shared e-scooter system.

Table 5
Summarization of POI categories.

Categories	Merged POI classes
Diversity	
Residential	'bungalow', 'allotment_house', 'mixed', 'semidetached_house', 'detached', 'dormitory', 'hut', 'semi', 'house', 'residential', 'apartments', 'cabin', 'shelter', 'hostel', 'terrace', 'chalet', 'guesthouse'
Commercial	'hotel', 'restaurant', 'bicycle_shop', 'fast_food', 'cafe', 'bar', 'supermarket', 'convenience', 'department_store', 'mall', 'pub', 'motel', 'outdoor_shop', 'bookshop', 'clothes', 'optician', 'car_rental', 'nightclub', 'bakery', 'laundry', 'hairdresser', 'beverages', 'florist', 'travel_agent', 'biergarten', 'furniture_shop', 'stationery', 'recycling_clothes', 'bicycle_rental', 'food_court', 'beauty_shop', 'doityourself', 'video_shop', 'sports_shop', 'mobile_phone_shop', 'shoe_shop', 'jeweller', 'toy_shop', 'car_dealership', 'gift_shop', 'greengrocer', 'butcher', 'computer_shop', 'vending_parking', 'vending_machine', 'vending_any', 'car_wash', 'market_place', 'recycling_metal', 'recycling_paper', 'car_sharing', 'kiosk', 'recycling_glass', 'garden_centre', 'recycling', 'newsagent', 'comms_tower', 'retail', 'hangar', 'factory', 'store', 'industrial', 'office', 'nursery', 'commercial', 'warehouse', 'shop', 'brewery', 'control_tower', 'dock', 'manufacture', 'bridge'
Recreational	'sports_hall', 'park', 'theatre', 'church', 'religious', 'cathedral', 'social_facility', 'subway_station', 'cultural', 'palace', 'gazebo', 'sport', 'sports_centre', 'stadium', 'ruins', 'synagogue', 'chapel', 'pavilion', 'mosque', 'cinema', 'museum', 'conference_centre', 'concert_hall', 'riding_hall', 'houseboat', 'boathouse', 'static_caravan', 'grandstand', 'boat', 'playground', 'attraction', 'picnic_site', 'zoo', 'fountain', 'viewpoint', 'artwork', 'archaeological', 'arts_centre', 'drinking_water', 'theme_park', 'pitch', 'ice_rink', 'golf_course', 'camp_site', 'dog_park', 'observation_tower', 'bench', 'swimming_pool', 'track', 'fort', 'caravan_site', 'hunting_stand'
Educational	'university', 'school', 'college', 'kindergarten', 'riding_school'
Public	'train_station', 'civic', 'library', 'community_centre', 'bank', 'atm', 'post_office', 'toilets', 'water_tower', 'government', 'public', 'railway_station', 'depot', 'observatory', 'embassy', 'parking', 'historic', 'transportation', 'fire_station', 'tower', 'museum', 'monument', 'memorial', 'toilet', 'police', 'post_box', 'courthouse', 'town_hall', 'tourist_info', 'wastewater_plant', 'prison', 'water_works', 'castle', 'water_well', 'waste_basket', 'lighthouse'
Health	'hospital', 'clinic', 'nursing_home', 'veterinary', 'pharmacy', 'dentist', 'doctors', 'chemist'
Other	'greenhouse', None, 'gasometer', 'storage_tank', 'military', 'garage', 'tower', 'roof', 'transportation', 'power_station', 'ship', 'service', 'garages', 'windmill', 'container', 'farm_auxiliary', 'shed', 'farm', 'guardhouse', 'barn', 'stable', 'carport', 'power', 'boat', 'bunker', 'parking_garage', 'construction', 'garage_shed', 'chimney', 'elevator', 'chicken_coop', 'covered_footbridge'
Road density	
Primary	'primary', 'motorway', 'trunk'
Secondary	'secondary', 'primary_link', 'trunk_link', 'secondary_link', 'motorway_link'
Tertiary	'tertiary', 'tertiary_link', residential', 'living_street', 'service'
Cycleway	'cycleway', 'bridleway', 'track'
Pedestrian	'pedestrian', 'footway', 'path', 'steps', 'track_grade2', 'track_grade4', 'track_grade1', 'track_grade3', 'unclassified', 'unknown', 'track_grade5'
Distance to transit	
Station	'bus_stop', 'tram_stop'
Enabling	'crossing', 'turning_circle', 'mini_roundabout', 'parking_bicycle'
Hindering	'traffic_signals', 'motorway_junction', 'parking_underground', 'slipway', 'weir', 'marina', 'lock_gate', 'stop'
Other	'speed_camera', 'fuel', 'parking', 'parking_multistorey', 'street_lamp'

Additionally, we found that approximately 56% of accessibility gains can be accounted for by built environment attributes, including land use diversity, road density, and distance to transit. Built environment factors related to urban mobility, such as land use mix (entropy), commercial land use ratio, and road density, have been found to be significantly associated with accessibility gains. ALE analysis revealed that these impacts are mostly nonlinear. Greater land use diversity and higher commercial land use ratios generally correspond to enhanced accessibility gains. However, several built environment factors demonstrate specific effective ranges and threshold effects. For instance, pedestrian road density shows a significant association with accessibility gains within the range of 0 to 33 km/km^2; beyond this threshold, the marginal gains approach zero. These findings not only elucidate the potential influence of land use on the effectiveness of ESS but also provide evidence-based guidance for enhancing the cost-effectiveness of land use interventions. Such insights are crucial for urban planners and policy-makers striving to optimize the integration of ESS with public transit, especially in the era of mobility as a service.

The following limitations should be considered for future research endeavors. Firstly, our study did not account for the monetary costs associated with ESS usage, potentially leading to underestimated levels of accessibility, poverty, and inequality. A more accurate assessment could be achieved by concurrently considering the travel time and monetary costs of ESS usage. Adopting such a comprehensive approach would not only enable researchers and policy-makers to gain better insights into the economic barriers faced by low-income populations, but also offer potential solutions such as pricing strategies and subsidies to improve the inclusiveness and affordability of ESS services. Secondly, specific information about ESS users was concealed due to privacy concerns. Future research efforts with access to more detailed user data could produce more granular results. Also, the enriched information could facilitate an analysis of ESS demand compared to existing infrastructure, potentially revealing infrastructure deficits and thus enabling more effective deployment strategies. Moreover, enriching the POI dataset from alternative sources could also advance this research, as the current study relies solely on OSM for POI extraction, which may not be sufficiently comprehensive. Finally, equity considerations were addressed by examining accessibility gains across different socioeconomic groups, but qualitative aspects of user experiences and preferences were not explored. Future studies could integrate qualitative methods, such as surveys or interviews, to capture the nuanced perspectives of diverse user groups and thus better inform equitable transport planning. Addressing these limitations in future research could provide a more comprehensive understanding of how ESS can contribute to sustainable and inclusive urban mobility solutions.

CRediT authorship contribution statement

Liyang Hu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yuan Liao:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Kun Gao:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sheng Jin:** Writing – review & editing, Visualization, Validation, Investigation. **Radu-Emil Precup:** Writing – review & editing, Validation, Supervision, Resources, Investigation.

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Appendix. Full list of POI categories

A full list of POI categories is summarized in the Table 5.

Data availability

Data will be made available on request.

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