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Disparities in public transport accessibility in London from 2011 to 2021

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ABSTRACT

Addressing urban inequalities has become a pressing concern on both the global sustainable development agenda and for local policy. Improving public transport services is seen as an important area where local governments can exert influence and potentially help reduce inequalities. Existing measures of accessibility used to inform decision-making for public transport infrastructure in London show spatial disparities, yet there is a gap in understanding how these disparities vary across demographic groups and how they evolve over time—whether they are improving or worsening. In this study, we investigate the distribution of public transport accessibility based on ethnicity and income deprivation in London over the past decade. We used data from the Census 2011 and 2021 for area-level ethnicity characteristics, English Indices of Deprivation for income deprivation in 2011 and 2019, and public transport accessibility metrics from Transport for London for 2010 and 2023, all at the small area level using lower super output areas (LSOAs) in Greater London. We found that, on average, public transport accessibility in London has increased over the past decade, with 78% of LSOAs experiencing improvements. Public transport accessibility in London showed an unequal distribution in cross-sectional analyses. Lower income neighbourhoods had poorer accessibility to public transportation in 2011 and 2023 after controlling for car-ownership and population density. These disparities were particularly pronounced for underground accessibility. Temporal analyses revealed that existing inequalities with respect to income deprivation and ethnicity are generally not improving. While wealthier groups benefited most from London Underground service improvements; lower income groups benefited more from bus service improvements. We also found that car ownership levels declined in areas with substantial increases to public transport accessibility and major housing developments, but not in those with moderate improvements.

1. Introduction and background

Addressing urban inequalities has become a pressing concern on both the global sustainable development agenda and within local policy frameworks. Recent trends indicate that 75% of global cities have experienced increased income inequality in the past two decades, underscoring the urgency of these issues within urban contexts (UN-Habitat, 2016). This challenge is highlighted in international initiatives such as the Sustainable Development Goals, Habitat III, C40 Cities, 100 Resilient Cities, United Cities and Local Governments, and the WHO Healthy Cities initiative. While conventional measures of inequality typically focus on income and wealth, there is growing recognition that disparities in non-monetary dimensions including transport are pivotal in shaping inequalities. The costs, availability, and efficiency of transport are linked to economic inequalities; population groups with limited financial resources encounter challenges affording transportation costs and time, restricting their ability to access job opportunities and worsening income disparities (Banister, 2018; Bills & Walker, 2017; Neutens, Schwanen, Witlox, & De Maeyer, 2010). Local governments are faced with multiple and sometimes conflicting challenges of addressing rising inequalities and pressures to mitigate and adapt to climate change. Public transport investments are pivotal in this regard, as they not only aim to contribute to reducing car ownership and usage for achieving net-zero transport, but also tackling inequalities by facilitating access to employment, education, and essential services (Banister, 1999; Banister, 2018; Pereira, Schwanen, & Banister, 2017).

The provision of public transportation services represents an important area where local governments often have significant intervention powers, making it a key policy priority in cities worldwide to support disadvantaged groups and efforts to reduce inequalities (Tonkiss, 2020). In academic research and practice, transport inequalities are primarily assessed through transport accessibility. Even though there is

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widespread consensus that transportation networks can mitigate inequalities by improving physical access, the task of defining and quantifying 'accessibility' poses significant challenges and researchers have developed multiple metrics of accessibility over the years (Bhat et al., 2000; Geurs & Van Eck, 2001; Gould, 1969). Conceptually, accessibility have been defined to consist of four key components (Geurs & Van Wee, 2004): land-use (spatial distribution and attributes of points-of-interest, including residential, commercial, and leisure activities), transportation system attributes (travel times, costs, comfort levels), temporal availability of activities at different times of day (opening hours), and individual constraints in accessing services like healthcare and retail (temporal or other). For empirical research and practical applications, multiple accessibility metrics are being developed and used (Geurs & Van Eck, 2001; Geurs & Van Wee, 2004; Van Wee & Geurs, 2011). Infrastructure-based accessibility metrics incorporate distance to public transport stops and the level of transport system including travel times, costs, network connectivity, and service levels (Linneker & Spence, 1992). Location-based metrics aim to incorporate available opportunities (such as jobs, shops, hospitals) that can be accessed within a time or distance threshold. Person-based metrics consider individual spatio-temporal constraints. Utility-based metrics introduce preferences of individuals. Transport inequalities research that uses accessibility levels aims to study its distribution over space and different population groups (Bhat et al., 2000; Bills & Walker, 2017; Carleton & Porter, 2018; Geurs & Van Eck, 2001; Hickman, Lira, Givoni, & Geurs, 2019; LaMondia, Blackmar, & Bhat, 2010; Litman, 1997; Lucas, Martens, Di Ciommo, & Dupont-Kieffer, 2019; Lucas, Van Wee, & Maat, 2016; Martens, 2012; Neutens et al., 2010; Pereira et al., 2017; Pritchard, Tomasiello, Giannotti, & Geurs, 2019; Talen & Anselin, 1998; Van Wee & Geurs, 2011). It is well acknowledged that poor access to reliable transportation can create barriers to participating in social activities, leading to social disparities and exclusion, especially among vulnerable groups such as the elderly and individuals with disabilities (Geurs & Van Wee, 2004; Lucas et al., 2016; Van Wee & Geurs, 2011; Welch, 2013). Additionally, health inequalities are influenced by transportation-related factors such as travel durations, access to healthcare, traffic related air pollution, road safety, and the availability of active travel options (Brauer, 2006; Clark & Stansfeld, 2007; De Nazelle et al., 2011). It is therefore a topic of research and policy priority in many cities around the world to ensure that new transport investments are planned to address transport related inequalities, ensuring all parts of society have access to transport services. For this purpose, the distribution of public transport accessibility levels is often mapped and visualized to identify areas that are particularly deprived and could benefit most from improvements. When combined with area-level metrics of socioeconomic status and race/ethnicity, often sourced from the census, it is also possible to quantify inequalities across different population groups. However, enhancing transport accessibility in neighbourhoods with low access does not necessarily benefit the current residents, as such improvements can increase housing prices, potentially displacing existing residents. Furthermore, new housing developments in these areas may intensify gentrification and displacement processes. As a result, improvements in transport accessibility in a particular area may not always benefit its residents, who might actually be adversely affected by gentrification and face displacement (Grube-Cavers & Patterson, 2015; Revington, 2015). It is therefore crucial to monitor changes in accessibility not only at the area level but also across different demographic groups within the city. While existing accessibility metrics are commonly used to assess proposed policy and investment decisions (El-Geneidy et al., 2016), they are rarely employed to track changes over time to understand how inequalities in accessibility are evolving across the city (Geurs & Van Wee, 2004), if investments in transport services benefit most deprived groups, and whether the gains are equally shared across different socioeconomic groups. This gap is significant because it overlooks the real impacts of transport investments on diverse population groups, neglecting the effects of population movements and the impacts of gentrification processes. These factors can influence how much deprived groups truly benefit from transportation interventions.

The level of public transport access inequality and whether it exists also depends substantially on the local city context. For example, in Toronto Canada, socially disadvantaged groups were found to have higher public transport accessibility in line with the suburbanisation patterns in the city (Foth, Manaugh, & El-Geneidy, 2013). In contrast, in Chicago, it was found that neighbourhoods with higher percentage of minorities, low-income workers, residents with lower educational attainment, and elderly have lower accessibility (Ermagun & Tilahun, 2020). Similarly, inequalities in accessibility across sociodemographic groups were revealed in cross sectional analyses in Brazil, Chile, and Australia (Giannotti et al., 2021; Scheurer, Curtis, & McLeod, 2017). In the London context, previous studies have identified spatial disparities in public transport accessibility and cross-sectional inequalities by occupation groups (Ford, Barr, Dawson, & James, 2015; Smith et al., 2020), and proposed methods for planning and policy evaluations in consideration for equality aspects (Church, Frost, & Sullivan, 2000; Sánchez-Mateos & Givoni, 2012). The temporal dimension, i.e. how public transport accessibility changes over time for disadvantaged groups received limited attention to date. In Toronto, it was found that socially disadvantaged populations have greater accessibility to jobs with shorter public transport travel times compared to other groups both in 1996 and 2006 (Foth et al., 2013). It is vital to understand disparities and how they evolve over time from observations to track population-level accessibility and ensure transportation improvements benefit all segments of society (Bills & Walker, 2017; Carleton & Porter, 2018; Castiglione, Hiatt, Chang, & Charlton, 2006; Dixit & Sivakumar, 2020; Litman, 1997; Lucas et al., 2019; Neutens et al., 2010; Pereira et al., 2017; Welch, 2013). However, there is a lack of longitudinal accessibility measurements and analyses on their implications for different social groups. Such analysis requires merging temporal data on accessibility as well as temporal high-resolution data on socioeconomic status.

In the Greater London Area, the Mayor of London's Transport Strategy outlines plans to enhance public transport and create new residential and employment opportunities (Transport for London, 2022). The strategy, first published in 2018 and revised in 2022, emphasizes promoting greater utilization of public transport and encouraging active travel modes such as walking and cycling. These improvements are expected to yield positive outcomes by addressing transport-related inequalities and reducing emissions from transport. Transport for London (TfL) is responsible for implementing these changes to align with the Mayor's vision outlined in 'A City for All Londoners' (Mayor of London, 2016). Consequently, there is a significant focus on enhancing neighbourhood connectivity and accessibility to public transport, as well as infrastructure that supports walking and cycling. Our study was motivated by the identified gap in measuring and quantifying the distribution of public transport accessibility among different population groups and tracking its evolution at small-area level. While existing measures of connectivity and accessibility in London are useful for identifying areas with limited accessibility and prioritizing them for improvements, they do not account for the socioeconomic groups affected. Particularly, if these groups are displaced due to rising prices in areas with improving accessibility, they might not benefit from, or could even be negatively impacted by, such investments. To ensure that accessibility improvements benefit vulnerable groups, including those from different socioeconomic and ethnic backgrounds, spatial accessibility metrics alone are insufficient. Temporal data on both spatial accessibility levels and neighbourhood socioeconomics are needed. This will enable us to examine whether accessibility improvements are benefiting various segments of society and if vulnerable groups are receiving the intended benefits from TfL and the Mayor's initiatives. Our goal is to address this gap by using recently available data for London, incorporating both transport accessibility metrics and small-area population statistics from two distinct time points over the past decade.

Specifically, our study has three main objectives. First, we investigated whether public transport access metrics demonstrated an inequitable distribution based on socioeconomic status and ethnicity across London in cross-sectional analyses. Second, we analysed the change in existing disparities over time and assessed whether vulnerable groups are experiencing improvements resulting from investments in London's transport infrastructure. We used data from the Census 2011 and Census 2021, as well as the English Indices of Deprivation for the years 2010 and 2019. Additionally, we incorporated Access Index for Public Transport Accessibility Levels (PTAL) from TfL for the years 2010 and 2023 (Transport for London, 2015). This is an infrastructure-based metric of accessibility, where the focus is on transport system performance including travel times, travel costs, distance to public transport stops, connectivity of the network, off-peak and peak service levels, reliability and speed (Linneker & Spence, 1992). We chose to use this metric because it is widely adopted in research and actively used to guide decision-making for transport infrastructure in London and our focus on changes in public transport provision. More details on its definition are provided below along with its potential shortcomings. Finally, we aim to assess the decline in car ownership rates across London and its relationship with improvements in public transport accessibility. This analysis seeks to better understand the impact of public transport service enhancements on car ownership, aligning with policy objectives in many local governments striving to achieve net-zero goals.

2. Methodology and data

2.1. Study setting

London's population increased by 7.7% between 2011 and 2021 as measured by the census, reaching a total of 8.8 million people. London consists of 4835 Lower Super Output Areas (LSOAs). LSOAs have population sizes ranging between 1000 and 3000 people and their spatial dimensions vary based on population density. We used LSOAs as our unit of analysis due to their relative stability over time and data availability at this geography on a range of socio-economic status (SES) indicators.

2.2. Public transportation accessibility

Transport for London (TfL) aims to track accessibility to describe and understand the level of transport provision is in different areas across London. TfL uses Access Indices (AI) as the quantitative metric for evaluations and comparisons as the underlying metric for the calculation of Public Transport Accessibility Levels (PTALs) in London. Each area is assigned a PTAL level score ranging from 0 (indicating very poor access) to 6b (indicating excellent access). These PTAL levels are determined based on the underlying AI value, which itself is a continuous value that ranges from 0 to approximately 100 in London. In this study, we used AI as the primary transport accessibility metric, as it is actively used in shaping transport policies and investment strategies in London. Specifically, TfL and its partners use AI values to identify areas that could potentially benefit from transportation improvements, evaluate impacts of new transport infrastructure and services, and inform planning decisions such as the prioritisation of new locations for housing, urban services, and parking facilities. However, these measures are not used to assess which population groups benefit from transport infrastructure investments over time, nor do they consider whether the observed impacts align with intended outcomes, considering population movements and gentrification effects. Our goal is to use an existing and actively used measure to evaluate if and to what extent transport inequalities are decreasing in London as overall accessibly increases, as reducing these inequalities is a policy priority at national and local level.

We obtained Access Index (AI) values for the years 2010 and 2023 from TfL. Its calculation is based on the service access points (all public transport stations and stops in London), transportation routes, and service frequency. The summary of formulas used for its calculation from the TfL PTAL guide is as follows, and full details can be found in TfL's methodology documentation (Transport for London, 2015):

$$\text{AWT (average waiting time) (mins)} = 0.5^{*}(60/\text{frequency}) + \epsilon \tag{1}$$

$$\text{EDF (equivalent doorstep frequency)} = 0.5^{*}\left(60/\left(\text{walk time}_{(\text{mins})} + \text{AWT}\right)\right) \tag{2}$$

$$\text{AI (access index)} = \mathit{max}\ (\text{EDF}) + 0.5^{*}\text{sum (other EDFs)} \tag{3}$$

$$\text{AI total} = \text{sum (AI bus} + \text{AI tube} + \text{AI tram)} \tag{4}$$

The average waiting time in minutes (AWT) in Eq. (1) is computed as half the interval between services (i.e., headway), which is equal to 60 divided by the service frequency. For example, if a bus arrives every 10 min at a given location, equivalent to 6 buses per hour, the average waiting time will be 5 min. While this is the scheduled waiting time, we also account for potential delays, adding an extra 2 min for buses and 0.75 min for rail services. The equivalent doorstep frequency (EDF) in Eq. (2) includes the walk time to the stop and converts it into a frequency value, representing the hypothetical service frequency at the 'doorstep' without any walk time. For each point in a London-wide grid, an AI index is computed separately for each mode of transport. Since each point may have access to multiple public transport stops, the EDF values for all stops are incorporated, with a weighting that prioritizes the highest value. We note that AI values do not account for changes in transport service hours and therefore cannot capture changes in accessibility resulting from such changes. More information is available from the TfL PTAL guide (Transport for London, 2014). We calculated an average AI value for each Lower Layer Super Output Area (LSOA) using the original 50 m grid data published by TfL. We computed area level AI values for AI total, as well as for AI bus, AI rail, and AI tube (referred to as AI Underground hereafter).

The resulting AI values at the LSOA level provide cross-sectional area level accessibility measures for the years 2010 and 2023. They also reflect how accessibility changed over time between these two time points, resulting from the opening of new stations, closures of existing ones, and changes in the frequency of public transport services.

2.3. Neighbourhood socio-economic context and ethnicity

The rationale for including race, ethnicity, and income variables in our analysis is that TfL acknowledges certain ethnic and socio-economic groups are particularly deprived in transport accessibility in London, a situation also influenced by gentrification processes (Transport for London, 2019). Local governments and TfL are interested in ensuring their investments benefit these deprived groups to support the Mayor's goal of reducing inequalities in London. However, merely improving transport access in neighbourhoods where deprived groups live does not necessarily lead to improvements for their residents, as they may be priced out or forced to leave these neighbourhoods when connectivity increases. Certain socio-economic and ethnic groups are particularly vulnerable to displacement due to inequalities in home ownership, access to secure housing, employment, and income characteristics.

We obtained data on income deprivation and ethnicity for the entire population in London at the small area level of LSOAs. Ethnicity information is sourced from the Census 2011 and 2021. We included three predominant ethnic groups in London in our analyses: (1) *White*, including English/Welsh/Scottish/Northern Irish/British, Irish, Gypsy

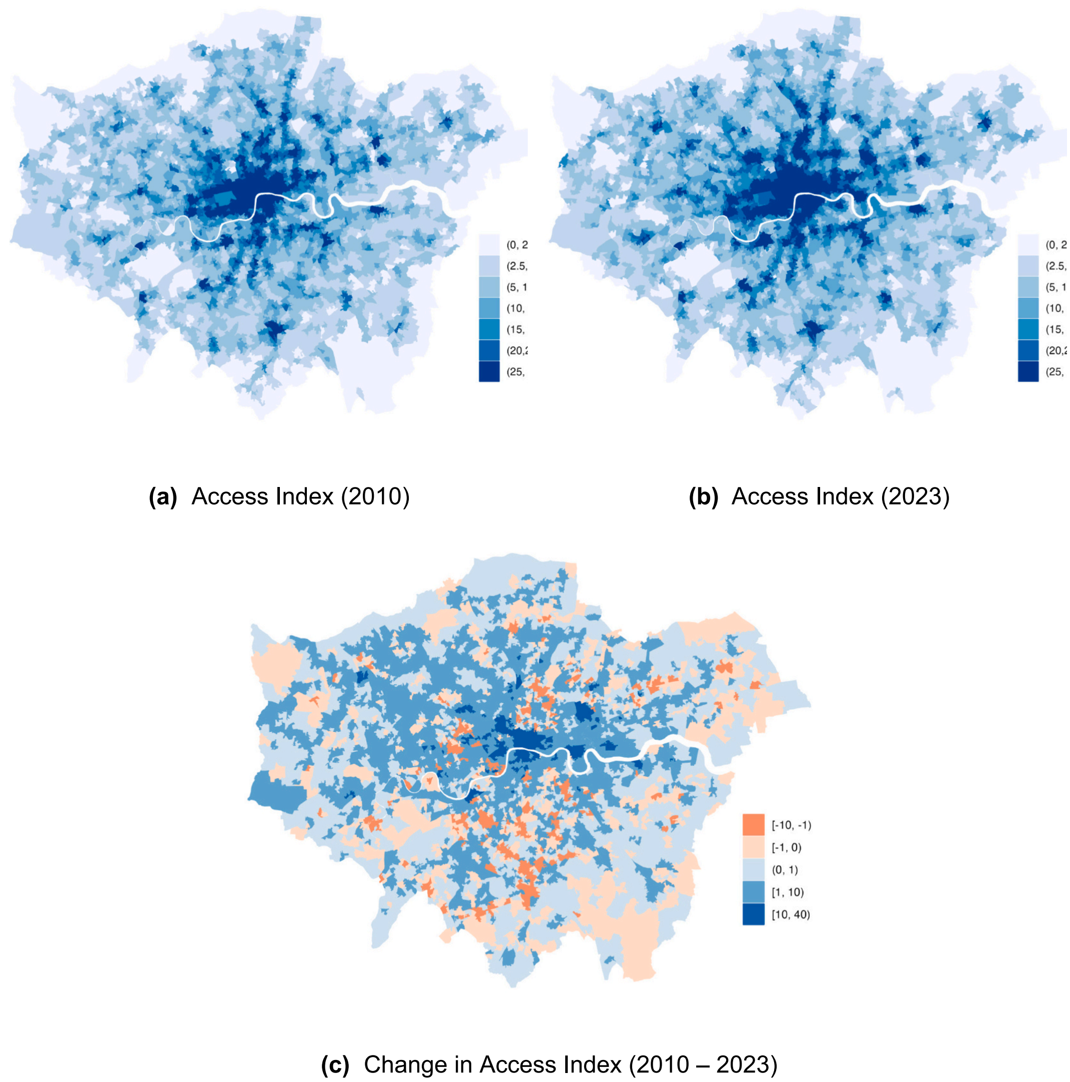

Fig. 1. Distribution of public transport accessibility for all LSOAs in London (n = 4835) as measured by Access Index (AI) computed and used by Transport for London (TfL) in (a) 2010, (b) 2023, and (c) its change between 2010 and 2023.

or Irish Traveller, Roma, Other White, (2) *Asian*, including Bangladeshi, Chinese, Indian, Pakistani, Other Asian, and (3) *Black* including African, Caribbean, Other Black. We computed percentages of each of these groups at the LSOA level by dividing the number of individuals in each group by the total LSOA population. The census in the UK does not collect information on income; we used the income deprivation metric available from the English Indices of Deprivation for the years 2010 and 2019. This provides a measure of low income due to being out-of-work or having low earnings. Underlying data include claimant datasets for government assistance programmes.

For income deprivation, we calculated quintiles of LSOAs, with quintile 1 corresponding to the worst-off 20% and quintile 5 to the best-off 20%. For ethnicity variables, we also categorised LSOAs into quintiles. Quintile 1 corresponds to areas with the lowest 20% representation of the specific ethnic group in the population, while quintile 5 corresponds to areas with the highest 20% representation of that group. Quintile 1 (Q1) was always used as the reference category.

2.4. Potential confounders

In our study investigating the relationship between public transport accessibility and income and ethnicity, it was important to account for two potential confounding factors that might distort the observed association, density and car ownership. Both variables influence both socio-economic factors and public transport accessibility. Additionally, self-selection is at play where individuals with different lifestyle preferences may choose neighbourhoods that align with their transportation needs and habits. Typically, population and housing density significantly impact availability and efficiency of public transport. Lower density areas exhibit lower levels of public transport accessibility due to lower demand in these areas. At the same time, densely populated neighbourhoods exhibit different socioeconomic characteristics compared to less dense areas. Patterns of suburbanization often link income to residential choices, influenced by historical context and personal preferences. In London, for example, there are wealthier residents live near the high-density city centres as well as some suburban areas. In contrast, in many U.S. cities wealthier residents tend to live in the

Table 1
Descriptive statistics for Access Index, ethnicity, population density, and car ownership measured at LSOA level across London, between 2010s and 2020s (n = 4835). Access Index values were reported by Transport for London (TfL) and were available for the years 2010 and 2023. All other variables were sourced from the Census 2011 and Census 2021.

Variable	Year	Mean	S.D.	Min	Max
Access Index – Total	2010	11.39	9.82	0.10	88.74
	2023	13.24	11.65	0.18	100
Access Index – Underground	2010	2.23	4.18	0.00	32.53
	2023	2.98	5.62	0.00	44.86
Access Index – Bus	2010	7.62	5.36	0.02	44.77
	2023	8.24	5.18	0.04	44.64
Access Index – Rail	2010	1.54	2.83	0.00	36.26
	2023	1.94	3.72	0.00	40.74
Income Deprivation Score	2010	0.19	0.11	0.01	0.58
	2019	0.14	0.08	0.01	0.44
% White	2011	60.69	20.37	3.54	98.16
	2021	55.15	18.75	1.94	96.62
% Asian	2011	17.94	16.17	0.75	86.90
	2021	19.66	16.06	0.65	87.88
% Black	2011	13.07	11.21	0.13	63.65
	2021	13.20	10.70	0.00	60.60
% Mixed	2011	4.92	1.95	0.61	14.39
	2021	5.74	2.03	0.68	18.51
% Other	2011	3.38	2.82	0.00	36.56
	2021	6.25	3.99	0.00	35.14
Population Density (population size per km2)	2011	9648	6652	116	93,958
	2021	10,002	6424	119	70,390
Car Ownership (% of households with 1 or more cars or vans)	2011	59.96	18.52	13.75	97.32
	2021	60.06	18.84	13.27	96.22

suburbs and city centres are more deprived despite having high public transport access (Church et al., 2000). The second is car ownership, higher income groups tend to have a greater levels of car ownership. At the same time, car owners rely less on public transport for accessing opportunities (Church et al., 2000; Paulley et al., 2006; Whelan, 2007). Lower income groups may rely more heavily on public transport due to financial constraints (Curl, Clark, & Kearns, 2018). Individuals often choose where to live based on their transport preferences. For example, those who prioritize public transport access might select neighbourhoods with better transport links, regardless of their income.

We downloaded data on population size from Census 2011 and Census 2021 for each LSOA. We calculated population density by dividing population size by LSOA land area in km^2. For car ownership levels, we used percentage of households with one or more cars or vans in the household sourced from the Census 2011 and 2021.

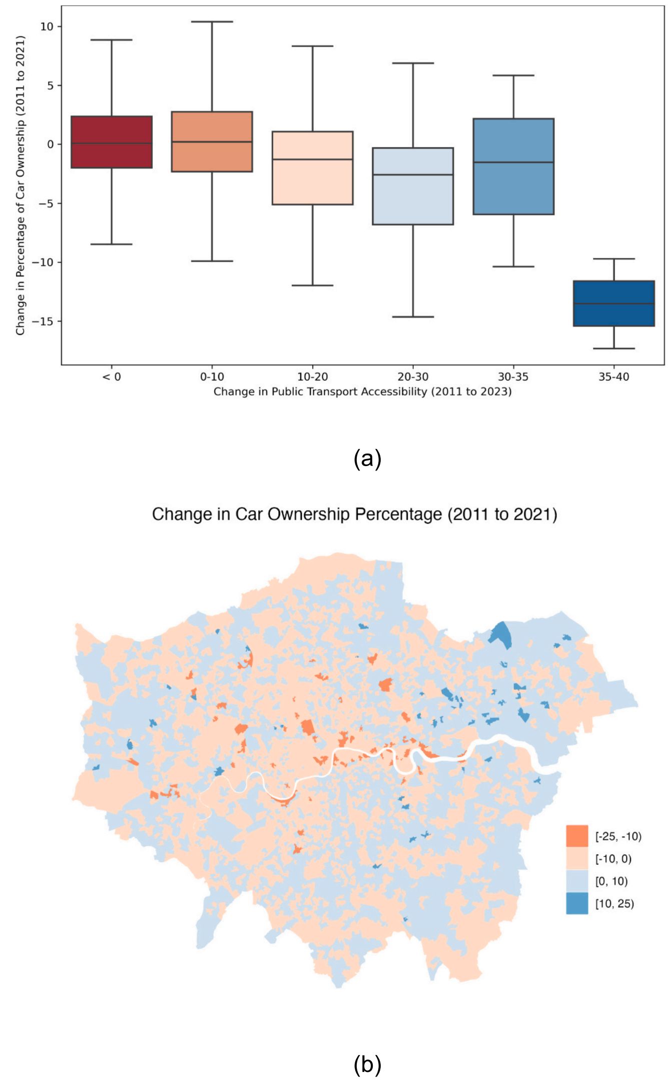

Fig. 2. (a) Relationship between changes in percentage of car ownership levels between 2011 and 2021, and changes in public transport accessibility. Darker blues indicate higher and positive changes in transport accessibility at Lower Super Output Area (LSOA) level, and reds indicate lower levels of improvements or decreases. (b) Distribution of change in car ownership levels across all LSOAs in London. Reds indicate decreases in car ownership levels, and blues indicate increases.

2.5. Statistical analysis

The primary objectives of our analyses were to assess associations between SES and ethnicity measures at the LSOA level and three public transport accessibility metrics: (1) 2010 LSOA level access index, (2) 2023 LSOA level access index, and (3) change in LSOA level access index (Δ Access Index) between 2010 and 2023. These are aimed to provide an understanding of how socio-economic factors and ethnic demographics are associated with both the cross-sectional states in two time points and temporal changes in accessibility at small area level over the past decade.

We used linear generalized additive models (GAMs) to evaluate associations between quintiles of SES and ethnicity indicators with Access Index and Δ Access Index. We use GAMs where we can use tensor product smooths to account for spatial effects while focusing on the remaining linear effects (Hastie, 2017; Wood, 2017), which is our main interest here. We included longitude and latitude information for all LSOAs using their centroids in the model using tensor product smooths, and all remaining variables were included as linear parameters. We estimated separate models for total Access Index (Eq. 4) as well as for buses, Underground, and rail separately. For all models we used access metrics as dependent variables, and income and ethnicity indicators as independent variables. To control for confounding factors, we specified models where we adjusted for effects of population density and car ownership.

For assessing the decline in car ownership levels and its relationship with improvements in public transport accessibility, we used bivariate analyses to better understand where car ownership levels were in the decline, and whether it was linked to improvements in public transport accessibility. Analyses were performed using R (version 4.3.2) and used the following packages (sf, sp., maptools, ggplot2, rgdal, mgcv, dplyr, and viridis). The overall workflow can be found in Fig. S.1.

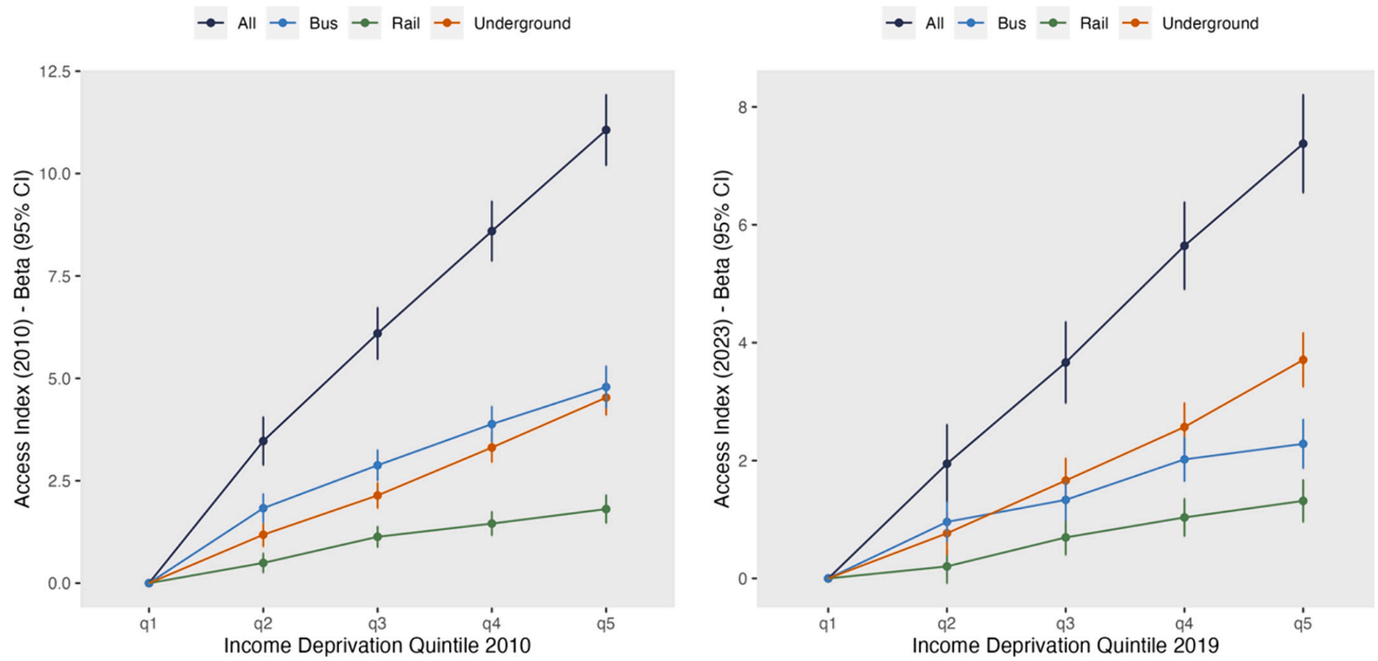

Fig. 3. Associations of income deprivation quintiles in 2010 and 2019 and Total Access Index in 2010 and 2023 and by different modes in all LSOAs (n = 4835) in London. See Table S.1–8 for corresponding numeric data. The error bars correspond to 95% CIs. Models included income deprivation quintiles and were adjusted for car ownership, population density, and latitude and longitude of the centroid. The parameter estimates for quintile 1 (q1), representing the most disadvantaged groups, were fixed at zero to serve as the reference category.

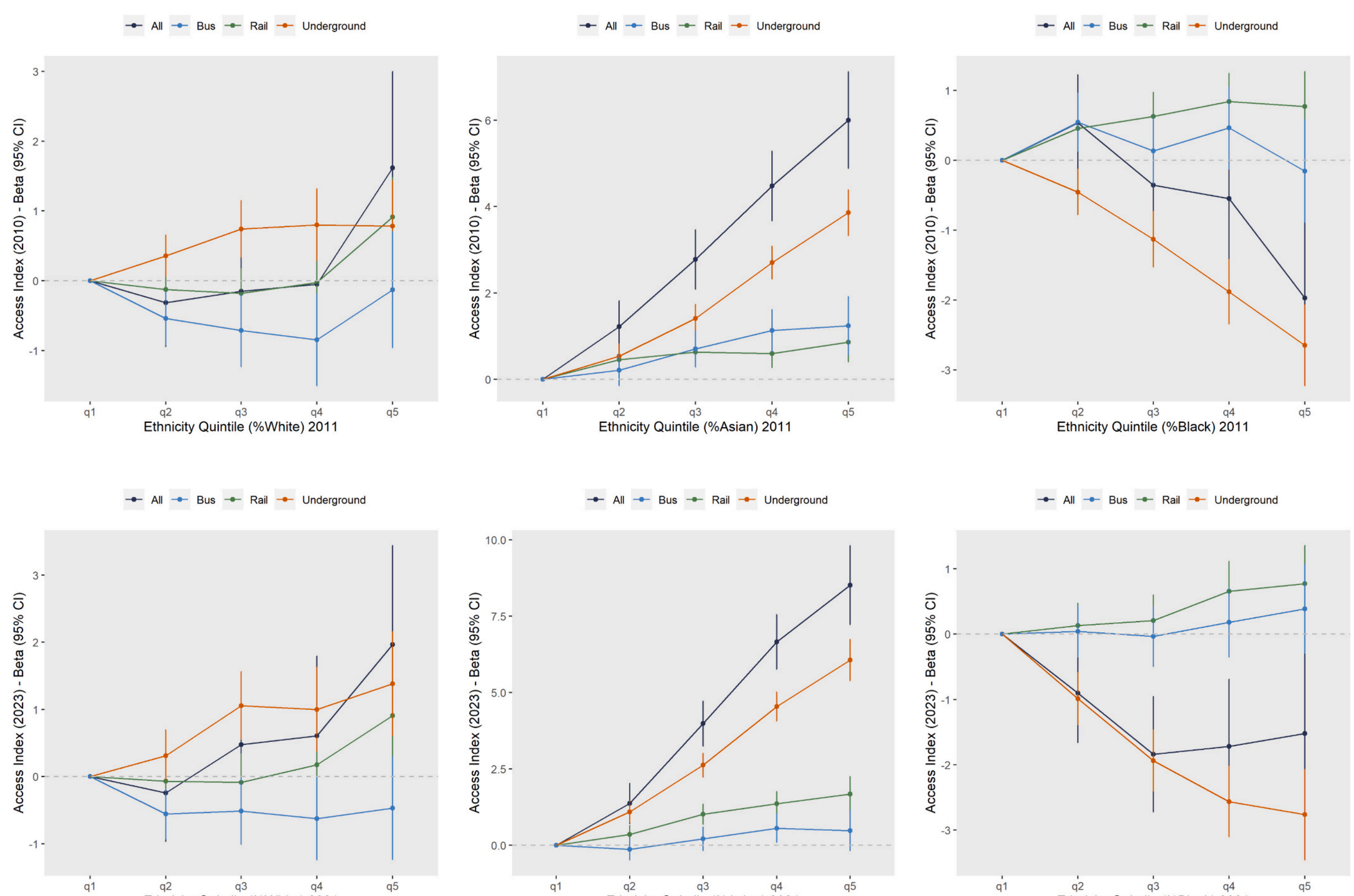

Fig. 4. Associations of % White, % Asian, % Black ethnicity quintiles in 2011 and 2021 with Access Index in 2010 and 2023 and by different modes in all LSOAs in London. See Table S.13–20 for corresponding numeric data. The error bars correspond to 95% CIs. Models included % White, % Asian, % Black quintiles and were adjusted for income deprivation quintiles, car ownership, population density, and latitude and longitude of the centroid. The parameter estimates for quintile 1 (q1), representing the areas with the lowest percentage of selected groups, were fixed at zero to serve as the reference category.

3. Results

3.1. Descriptive statistics and bivariate analyses

We included all LSOAs in Greater London. Public transport accessibility as measured by Access Index 2010 and 2023 showed different geographic patterns and trends across London (Fig. 1). Accessibility was highest in central London and along the radial public transport corridors towards outer London. The Change in Access Index map shows interesting patterns across the city, where accessibility increased in central areas where it was already high to begin with, but also in neighbourhoods that benefited most from new Underground and rail infrastructure. The areas depicted in orange in Fig. 1c show a decline in accessibility and are mostly associated with reductions in bus service frequencies and bus route cancellations since the coronavirus pandemic that have not been restored to their original levels.

Overall, public transport accessibility increased on average in London, with 78% of LSOAs experiencing improvements between 2010 and 2023 (see Table 1). Accessibility increases, as expected, were higher in Opportunity Areas identified by the Mayor of London (Mayor of London, 2021), which were specifically targeted for development (Fig. S2). Average Access Index for buses, the Underground, and rail also exhibited upward trends. Notably, significant investments in Underground and rail services during this period are evident in the maximum values achieved for their Access Index, despite the moderate average increases observed for these modes.

Fig. 2 illustrates the relationship between changes in car ownership levels between 2021 and 2011 and changes in overall Access Index between 2023 and 2010. Car ownership levels declined in areas with substantial increases to public transport accessibility and major planned housing developments, such as the Royal Docks and Colindale. However, this was not a linear trend, we did not observe consistent decreases in car ownership levels in neighbourhoods with moderate improvements.

3.2. Associations of poverty with public transport accessibility

In cross-sectional analyses using GAM models, wealthier LSOAs had higher levels of public transport accessibility after controlling for car ownership and population density both in 2010 and 2023 (Fig. 3, Table S.1–8). These differences were more pronounced for the Underground compared to buses and rail services in 2023. Fig. 3 shows parameter estimates for models where we control for population density and car ownership. The parameter estimates for quintile 1 (q1), representing the most disadvantaged groups, were fixed at zero to serve as the reference category.

LSOAs in the wealthiest quintile had higher accessibility corresponding to a 7.38 higher accessibility [95% confidence interval (CI): 6.95, 7.80] compared to the poorest quintile in 2023. There was a clear trend for all transport modes where wealthier neighbourhoods had better access to public transportation services. Associations with SES indicators were generally strongest for the Underground services in 2023 and weakest for rail.

3.3. Associations of ethnicity with public transport accessibility

In the 2021 census, London's population was distributed as 53.8 White ethnic groups, 20.8% Asian groups, 13.5% Black groups, 5.7% Mixed groups, and 6.3% other ethnic groups. We selected the top three ethnicities, % White, % Asian, and % Black, representing the majority from the five ethnic categories, and all models presented in Fig. 4 were adjusted for income, car ownership, and population density.

No clear patterns were identified in the association between overall accessibility and % White ethnicities. LSOAs with the highest quintile of % White had slightly better access to bus services corresponding to a 1.381 [95% CI: 1.0, 1.8] higher accessibility compared to lowest quintile of % White in 2023. In contrast, neighbourhoods with a higher level of Asian residents demonstrated evidently positive correlation with public transport accessibility, particularly for Underground services. LSOAs with the highest quintile of % Asian residents had higher accessibility corresponding to a 6.00 higher accessibility compared to lowest quintile of % Asian residents in 2011. And this figure rose to 8.515 in 2023.

Areas with a higher % Black ethnicity were associated with lower accessibility for Underground services, after adjusting for income, car ownership, and population density.

3.4. Associations of poverty and ethnicity with change in public transport accessibility

Fewer clear patterns emerged from the analysis of change in accessibility between 2010 and 2023 compared to the results from cross-sectional analyses (See Figs. 5 and 6). There was a positive association between wealthier areas and change in access to Underground services. This relationship was reversed for bus access, suggesting that poorer neighbourhoods benefit most from improvements in bus services.

Positive associations were identified between % Asian ethnicities and improvements in access to rail and Underground services. Conversely, a negative relationship was observed for bus access. Notably, for Black ethnic groups, a positive relationship was found exclusively with changes in access to bus services. Compared to other two ethnic groups, neighbourhoods with a higher % Black ethnicities experienced the greatest benefits from improved bus services, while areas with a higher % Asian ethnicities benefited the most from enhancements in Underground and rail services. Moreover, areas with a

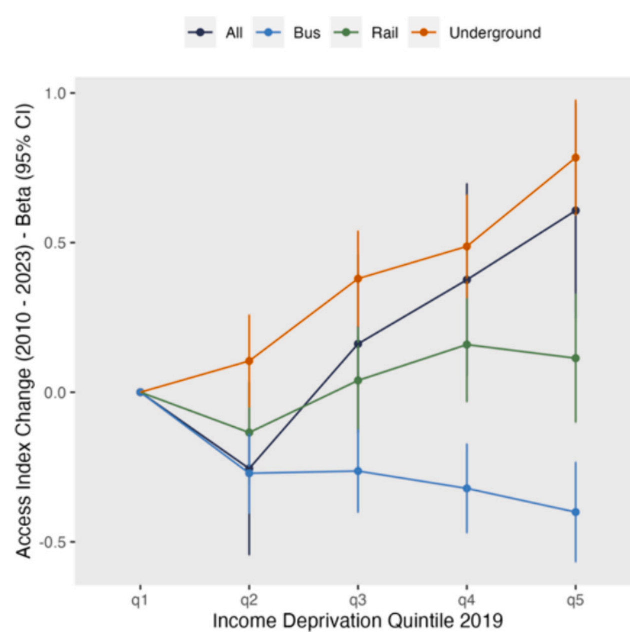

Fig. 5. Associations of income deprivation quintiles in 2019 and Total Access Index Change between 2010 and 2023 and by different modes in all LSOAs (n = 4835) in London. See Table S.9–12 for corresponding numeric data. The error bars correspond to 95% CIs. Models included income deprivation quintiles and were adjusted for car ownership, population density, and latitude and longitude of the centroid. The parameter estimates for quintile 1 (q1), representing the most disadvantaged groups, were fixed at zero to serve as the reference category.

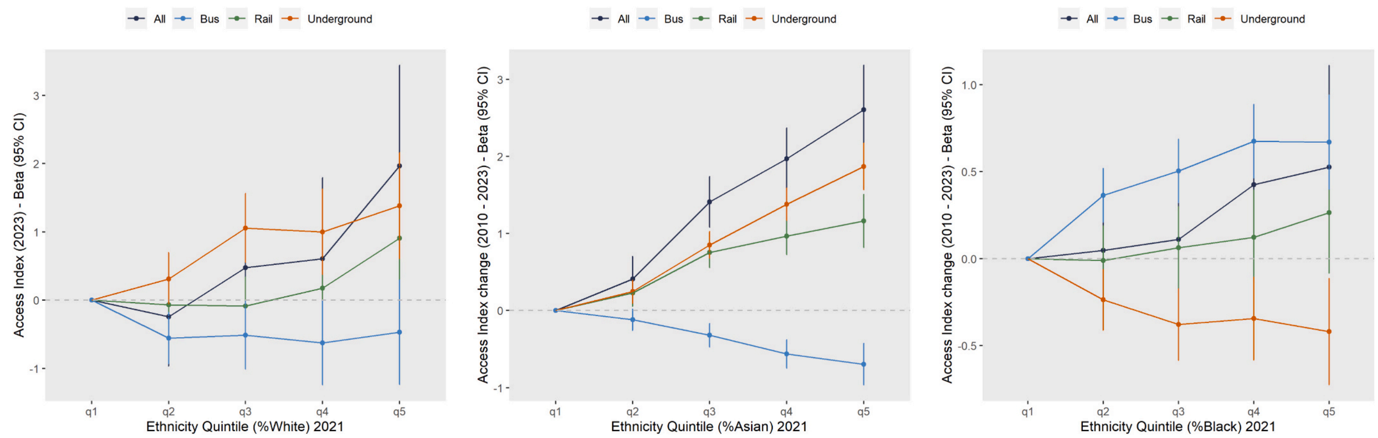

Fig. 6. Associations of % White, % Asian, % Black, ethnicity quintiles in 2021 and Total Access Index Change between 2010 and 2023 and by different modes in all LSOAs (n = 4835) in London. See Table S.21–24 for corresponding numeric data. The error bars correspond to 95% CIs. Models included % White, % Asian, and % Black ethnicity quintiles and were adjusted for income deprivation quintiles, car ownership, population density, and latitude and longitude of the centroid.

greater % Black ethnicities were found to be more deprived in terms of access to Underground, while neighbourhoods with higher % White ethnicities benefited more from improvements in Underground services.

4. Discussion

To the best of our knowledge, this study represents the first exploration of the relationship between both cross-sectional and temporal trends in public transport accessibility in London and its distribution across different income and ethnic groups. We specifically investigated the relationship between multiple accessibility metrics with cross-sectional area-level measures of income and ethnic composition. In contrast to previous analyses addressing inequalities in public transport accessibility, our study has a novel focus on how it changes over time and which population groups benefit most from infrastructure investments and improvements to public transport service provision. We leveraged high resolution information on public transport accessibility as measured and reported by TfL, along with small area statistics on income deprivation and ethnic composition available from English Indices of Deprivation for the years 2010 and 2019, and from the Census 2011 and Census 2021. This approach allowed us to generate city-wide temporally varying transport accessibility metrics by different modes capturing overall access as well as access by bus, rail, and Underground services. We studied both cross-sectional and temporal relationships between public transport accessibility, income, and ethnicity at the LSOA-level across London.

The Access Index measure developed by TfL offers the advantage of being used in practice to track and evaluate impacts of infrastructure investments and changes in public transport service provision. We examined Access Index for different public transport modes separately, in addition to Access Index Total that includes all types of public transport modes including bus, rail, Underground, and Trams. The observed differences in distribution of access by different modes suggest that improvements in different types of public transportation are likely to benefit different groups in the population.

In the univariate and bivariate analyses, we found that accessibility in London improved on average and in most neighbourhoods over the past decade. We also found that accessibility improved most both in central London where it was already high in 2010 and in Opportunity Areas as defined in Mayor of London's strategy. These areas particularly benefited from substantial infrastructure investments in Underground and rail networks across the city. Decline in public transport accessibility were associated with reductions in bus services during the coronavirus pandemic, which have not been fully restored. We also observed a rise in car-ownership levels across over the past decade; the only areas where car ownership declined were those that experienced significant enhancements in accessibility. This may be potentially driven by growing attractiveness of these areas due to improved public transport infrastructure and new residents locating to high-density development areas thereby requiring less car-use due to the availability of attractive public transport and active travel alternatives, and consequently contributing to the observed reduction in car ownership.

In models controlling for car ownership rates and population density, wealthier areas, and neighbourhoods with higher levels of Asian residents tended to have higher public transport accessibility. These associations were more pronounced for Underground services. We also found areas with higher % of Black residents had lower levels of accessibility for Underground services after controlling for income, car ownership levels, and population density. Associations between proportions of White ethnicity were weaker.

When examining temporal trends, we noticed weaker associations overall suggesting that existing inequalities are not improving. One exception was improvements in bus services benefiting poorer groups and neighbourhoods with a higher percentage of Black residents. Patterns related to the percentage of ethnic groups were less clear. Our findings contribute to the literature suggesting a perceived lack of improvement or change in public transport accessibility for the most disadvantaged communities. This highlights the need for targeted efforts to address inequalities in public transport access to enhance accessibility and connectivity in the most disadvantaged areas.

Our study has several limitations. First, the accessibility measure used in our work, developed by TfL, focuses solely on the distance to infrastructure. It lacks consideration of crucial factors such as attractiveness of destinations, travel time, ease of travel, and cost associated with different transportation options. The advantage of using this metric for our analysis is that it is currently employed as a planning tool, is relatively easy to understand, has been applied in other countries globally, and can be adopted in other contexts due to its low data needs, only requiring service frequency data from transport agencies (Inayathusein & Cooper, 2018). As it does not consider the spatial distribution of opportunities or their attractiveness, the accessibility of an LSOA is based solely on the availability of public transport nodes and connections, without considering whether these connect to more desirable destinations. For example, a frequent bus service to the neighbouring residential area will result in a better accessibility score compared to a less frequent service to city centres. Also, the cost of transport is not included. This is an important factor, especially in the analysis of deprivation, as people with low income are typically more sensitive to the monetary cost of travel. For example, lower-income groups who reside near rail stations may opt to use buses instead due to the high costs of rail travel. This could lead to an overestimation of their experienced accessibility. That said, the accessibility metrics that aim to incorporate such additional dimensions, also discussed in the background section – including location-based, person-based, and utility-based measures – are more difficult to quantify and are rarely available for strategic planning due to their higher data requirements. We need more data and further research that uses a combination of different accessibility measures, in addition to those currently used in practice, for a comprehensive understanding of disparities and how they change. Second, the effectiveness of new public transport investments in improving accessibility has not been sufficiently captured. The impact of these investments extends beyond merely adding stations and routes; it also includes factors like the ease of transferring between different modes of transportation. A further limitation relates to the representation of individuals' utilization and need for public transport services available to them. This limitation arises from relying on area level measures rather than using individual level metrics and observations. Ideally, we would want to incorporate individual level characteristics and need of the resident population and whether available public transport services are sufficient to meet their needs. Addressing this, however, is challenging as observed mobility patterns do not also fully capture suppressed demand. Lastly, our study does not capture within-city migration between different neighbourhoods in London. Consequently, we are unable to fully study the dynamics associated with increasing housing prices and the displacement of residents resulting from improvements in public transport accessibility. We cannot assess whether displaced populations ultimately are worse off. This limitation underscores the need for further research and data that captures within city migration to comprehensively understand the multifaceted impacts of transportation improvements on urban dynamics and disparities.

Our study also has multiple strengths and adds substantial contributions to the growing body of literature on disparities in access to public transportation. First, we utilized a metric which is being actively used to inform planning decisions. Second, our analysis included both cross-sectional and temporal associations, drawing from a large sample that included all LSOAs in London. This approach enabled us to investigate whether income and ethnic composition were associated with public transport accessibility and its changes over the period spanning 2010 to 2023. We also implemented modal stratification in our analyses, revealing differences in how accessibility to different modes is distributed across different areas and population groups. Our analyses were adjusted for confounding factors such as population density and car ownership. This adjustment is important because self-selection bias may influence the results.

5. Conclusions

Overall, we observed an inequitable distribution of public transport accessibility in London by income and ethnicity measures in London. The strength of the association was different between different public transport modes. Cross-sectional associations with both income and ethnicity measures were stronger than temporal associations. Temporal findings suggest that the existing inequalities are not improving. Even though average public transport accessibility has increased in most areas in London, there is little evidence that deprived groups benefit from these investments apart from bus services. Poorest areas in London benefited most from improvements in bus services. Increasing public transport accessibility to benefit the most disadvantaged groups, however, could be challenging as it may lead to an increase in housing prices and displacement of resident populations through processes of gentrification. Balancing the aim of improving public transport accessibility in disadvantaged areas with the risk of unintended consequences such as displacement poses a complex challenge. The results relating to bus services are in line with prior work, which have found that poorer residents make more use of bus services. Improving bus services, therefore, presents an opportunity for urban and transport planners to improve public transport accessibility for the most disadvantaged groups while also minimising the risks associated with increased housing prices, gentrification, and displacement.

Data and code availability

All datasets used in this paper are publicly available and the sources are provided in the main text. Upon publication, the code will be available at https://github.com/yuxinnie/access-equity-paper.

CRediT authorship contribution statement

Yuxin Nie: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Shivani Bhatnagar:** Writing – review & editing, Data curation, Conceptualization. **Duncan Smith:** Writing – review & editing, Conceptualization. **Esra Suel:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

Shivani Bhatnagar is employed by Transport for London (TfL) related to transportation planning in London. We confirm that this competing interest did not inappropriately influence the design, execution, or reporting of the study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2024.102169.

References

Banister, D. (1999). Planning more to travel less: Land use and transport. *The Town Planning Review*, 313–338.

Banister, D. (2018). *Inequality in transport*. Marcham, Oxfordshire: Alexandrine press.

Bhat, C., Handy, S., Kockelman, K., Mahmassani, H., Chen, Q., & Weston, L. (2000). *Urban accessibility index: Literature review*. Springfield: Center of Transportation Research, University of Texas at Austin.

Bills, T. S., & Walker, J. L. (2017). Looking beyond the mean for equity analysis: Examining distributional impacts of transportation improvements. *Transport Policy, 54*, 61–69.

Brauer, M. (2006). Health effects of transport-related air pollution. *Canadian Journal of Public Health, 97*(5), 418.

Carleton, P. R., & Porter, J. D. (2018). A comparative analysis of the challenges in measuring transit equity: Definitions, interpretations, and limitations. *Journal of Transport Geography, 72*, 64–75.

Castiglione, J., Hiatt, R., Chang, T., & Charlton, B. (2006). Application of travel demand microsimulation model for equity analysis. *Transportation Research Record, 1977*(1), 35–42.

Church, A., Frost, M., & Sullivan, K. (2000). Transport and social exclusion in London. *Transport Policy, 7*(3), 195–205.

Clark, C., & Stansfeld, S. A. (2007). The effect of transportation noise on health and cognitive development: A review of recent evidence. *International Journal of Comparative Psychology, 20*(2).

Curl, A., Clark, J., & Kearns, A. (2018). Household car adoption and financial distress in deprived urban communities: A case of forced car ownership? *Transport Policy, 65*, 61–71.

De Nazelle, A., Nieuwenhuijsen, M. J., Antó, J. M., Brauer, M., Briggs, D., Braun-Fahrlander, C., … Fruin, S. (2011). Improving health through policies that promote active travel: A review of evidence to support integrated health impact assessment. *Environment International, 37*(4), 766–777.

Dixit, M., & Sivakumar, A. (2020). Capturing the impact of individual characteristics on transport accessibility and equity analysis. *Transportation Research Part D: Transport and Environment, 87*, Article 102473.

El-Geneidy, A., Levinson, D., Diab, E., Boisjoly, G., Verbich, D., & Loong, C. (2016). The cost of equity: Assessing transit accessibility and social disparity using total travel cost. *Transportation Research Part A: Policy and Practice, 91*, 302–316.

Ermagun, A., & Tilahun, N. (2020). Equity of transit accessibility across Chicago. *Transportation Research Part D: Transport and Environment, 86*, Article 102461.

Ford, A. C., Barr, S. L., Dawson, R. J., & James, P. (2015). Transport accessibility analysis using GIS: Assessing sustainable transport in London. *ISPRS International Journal of Geo-Information, 4*(1), 124–149.

Foth, N., Manaugh, K., & El-Geneidy, A. M. (2013). Towards equitable transit: Examining transit accessibility and social need in Toronto, Canada, 1996–2006. *Journal of Transport Geography, 29*, 1–10.

Geurs, K. T., & Van Eck, J. R. R. (2001). *Accessibility measures: review and applications. Evaluation of accessibility impacts of land-use transportation scenarios, and related social and economic impact. RIVM rapport 408505006*.

Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography, 12*(2), 127–140.

Giannotti, M., Barros, J., Tomasiello, D. B., Smith, D., Pizzol, B., Santos, B. M., … Batty, M. (2021). Inequalities in transit accessibility: Contributions from a comparative study between Global South and North metropolitan regions. *Cities, 109*, Article 103016.

Gould, P. R. (1969). *Spatial diffusion, Resource Paper No. 4*.

Grube-Cavers, A., & Patterson, Z. (2015). Urban rapid rail transit and gentrification in Canadian urban centres: A survival analysis approach. *Urban Studies, 52*(1), 178–194.

Hastie, T. J. (2017). Generalized additive models. In *Statistical models in S* (pp. 249–307). Routledge.

Hickman, R., Lira, B. M., Givoni, M., & Geurs, K. (2019). *A companion to transport, space and equity*. Edward Elgar Publishing.

Inayathusein, A., & Cooper, S. (2018). *London's accessibility indicators: Strengths, weaknesses, challenges*.

LaMondia, J. J., Blackmar, C. E., & Bhat, C. R. (2010). *Comparing transit accessibility measures: a case study of access to healthcare facilities. in Transport Research Board 2011 Annual Meeting. Washington, DC*.

Linneker, B., & Spence, N. (1992). An accessibility analysis of the impact of the M25 London orbital motorway on Britain. *Regional Studies, 26*(1), 31–47.

Litman, T. (1997). *Evaluating transportation equity*. Victoria Transport Policy Institute Victoria.

Lucas, K., Martens, K., Di Ciommo, F., & Dupont-Kieffer, A. (2019). *Measuring transport equity*. Elsevier.

Lucas, K., Van Wee, B., & Maat, K. (2016). A method to evaluate equitable accessibility: Combining ethical theories and accessibility-based approaches. *Transportation, 43*, 473–490.

Martens, K. (2012). Justice in transport as justice in accessibility: Applying Walzer's 'spheres of Justice'to the transport sector. *Transportation, 39*, 1035–1053.

Mayor of London. (2016). *A City for All Londoners*.

Mayor of London. (2021). *The London Plan: The Spatial Development Strategy for Greater London*.

Neutens, T., Schwanen, T., Witlox, F., & De Maeyer, P. (2010). Equity of urban service delivery: A comparison of different accessibility measures. *Environment and Planning A, 42*(7), 1613–1635.

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., … White, P. (2006). The demand for public transport: The effects of fares, quality of service, income and car ownership. *Transport Policy, 13*(4), 295–306.

Pereira, R. H., Schwanen, T., & Banister, D. (2017). Distributive justice and equity in transportation. *Transport Reviews, 37*(2), 170–191.

Pritchard, J. P., Tomasiello, D., Giannotti, M., & Geurs, K. (2019). *An international comparison of equity in accessibility to jobs: London*. Findings: São Paulo and the Randstad.

Revington, N. (2015). Gentrification, transit, and land use: Moving beyond neoclassical theory. *Geography Compass, 9*(3), 152–163.

Sánchez-Mateos, H. S. M., & Givoni, M. (2012). The accessibility impact of a new High-Speed Rail line in the UK–a preliminary analysis of winners and losers. *Journal of Transport Geography, 25*, 105–114.

Scheurer, J., Curtis, C., & McLeod, S. (2017). Spatial accessibility of public transport in Australian cities: Does it relieve or entrench social and economic inequality? *Journal of Transport and Land Use, 10*(1), 911–930.

Smith, D. A., Shen, Y., Barros, J., Zhong, C., Batty, M., & Giannotti, M. (2020). A compact city for the wealthy? Employment accessibility inequalities between occupational classes in the London metropolitan region 2011. *Journal of Transport Geography, 86*, Article 102767.

Talen, E., & Anselin, L. (1998). Assessing spatial equity: An evaluation of measures of accessibility to public playgrounds. *Environment and Planning A, 30*(4), 595–613.

Tonkiss, F. (2020). City government and urban inequalities. *City, 24*(1–2), 286–301.

Transport for London. (2014). Public Transport Accessibility Levels. Available from: https://data.london.gov.uk/dataset/public-transport-accessibility-levels.

Transport for London. (2015). *Assessing transport connectivity in London*.

Transport for London. (2019). *Travel in London: Understanding our diverse communities 2019*.

Transport for London. (2022). The Mayor's Transport Strategy. Available from https://tfl.gov.uk/corporate/about-tfl/the-mayors-transport-strategy.

UN-Habitat. (2016). *Urbanization and Development: Emerging Futures*.

Van Wee, B., & Geurs, K. (2011). Discussing equity and social exclusion in accessibility evaluations. *European Journal of Transport and Infrastructure Research, 11*(4).

Welch, T. F. (2013). Equity in transport: The distribution of transit access and connectivity among affordable housing units. *Transport Policy, 30*, 283–293.

Whelan, G. (2007). Modelling car ownership in Great Britain. *Transportation Research Part A: Policy and Practice, 41*(3), 205–219.

Wood, S. N. (2017). *Generalized additive models: an introduction with R*. CRC press.