Inequalities in Public Transport Accessibility over a Decade: Through the Spatial Distribution of Ethnicity, Age, and Socioeconomic Status

A Case Study in Greater London Area

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Abstract

Cross-sectional studies have indicated spatial inequalities in public transport accessibility within London, where low-skilled, low-income groups often experience limited accessibility, hindering their access to urban services and opportunities. However, how accessibility to public transport is distributed by demographic groups and how it changed over time have not been studied. This study examined the potential unequal distribution of public transport accessibility with a focus on demographic groups defined by ethnicity, age, and socioeconomic status by cross-sectional models over the past decade, at the LSOA level in the Greater London Area. After accounting for geographical features, car ownership, population density, and spatial autocorrelation in spatial lag models, the disparities for ethnicity were found, as the mixed and other ethnic groups were more disadvantaged both in 2011 and 2021, while the Asian ethnic groups had a more advantaged position. Income also played a role, as wealthier groups tended to have better access to public transport; however, these privileges decreased throughout the decade. The accessibility advantage of the middle-aged and older groups in 2011 diminished significantly by 2021. This was replaced by the median low-level age group, which had the most prominent advantage in tube accessibility. The research aims to inform policymakers on addressing disparities in public transport, optimising accessibility, and developing a fairer and more inclusive urban environment.

Declaration of Authorship

I, Yuxin Nie, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 10279 words in length, excluding references and Appendix.

Yuxin Nie

Yuxin Nie

25 August 2023

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Chapter 1: Introduction

1.1 Background

Public transportation is one of the most important infrastructures for cities (Aoun, 2013). By connecting individuals to education, employment, healthcare, services, and socio-cultural activities (Ceder, 2021), public transport becomes the key to providing access to opportunities for all urban residents. However, studies of the global cities suggest public transport investment brings up housing prices near the stations (So, Tse and Ganesan, 1997; Yiu and Wong, 2005; Dorantes, Paez and Vassallo, 2011; Zhou *et al.*, 2022), which often leads to gentrification and social exclusion (Padeiro, Louro and Da Costa, 2019). The similar situation also happens in London, proved by evidence from the research on DLR (Song *et al.*, 2019), showing disparities existing in terms of equity and inclusivity. Low-skilled, low-income groups often experience limited accessibility (Smith *et al.,* 2020), hindering their access to urban services and opportunities (Serag El Din *et al.*, 2013).

In London, over the last decade, efforts by transport departments such as Transport for London (TFL) to invest in public transport have improved overall accessibility (Greater London Authority, 2018), but challenges like transit-induced gentrification persist (Lagadic, 2019).

The 2021 Census data for England and Wales shows the most ethnically diverse region was London – 46.2% of residents identified with Asian, black, mixed, or 'other' ethnic groups, and a further 17.0% with white ethnic minorities (Office for National Statistics, 2022). Spatially, the extent of ethnic diversity across London boroughs varies significantly. Within this context, disparities in housing are particularly evident, with ethnic minority groups disproportionately concentrated in the most deprived areas of the city.

As urban areas continue to experience increasing cultural diversity, the examination of whether these diverse communities have equitable opportunities to participate in the benefits of accessible and efficient transportation systems becomes important. Understanding public transit accessibility of minorities among demographic groups is crucial to grasp the urban dynamics.

Related works of literature suggest there are spatial inequalities in public transport accessibility in London. However, how access to public transport is distributed by demographic groups, especially ethnicity, age, and socioeconomic status, and how it changed over time, have not been fully studied.

Therefore, this study focuses on inequalities in the spatial distribution of public transport accessibility across race, income, and age. Spatial models were constructed using a selection of appropriate spatial regression methods based on the analysis of spatial variables. These models quantify the relationship between demographic characteristics and accessibility in the spatial unit of the neighbourhoods for the 2011 and 2021 distributions. Additionally, the 2011 demographic distributions and the amount of change in accessibility over the last ten years are also modelled. The results of the two parts of the study are then combined in an analysis and interpretation. The findings are analysed and interpreted in conjunction with the results of the two parts of the study to determine which races are experiencing what level of inequality in accessibility.

1.2 Research Questions and objectives

The objectives of this study can be summarised as the following research questions:

a) What are the relationships between public transport accessibility and demographic characteristics in terms of ethnicity, age and income in Greater London Area?

b) How has this relationship changed over the past ten years, in the context of the introduction of new public transport?

This paper aims to contribute to this literature and quantify inequalities in accessibility to public transport in London. Our goal is to not only look at cross-sectional data but also evaluate how accessibility changed over the past decade for different demographic groups characterised by ethnicity, age and income. The findings will inform policymakers on optimising accessibility and addressing disparities in urban transport.

Ultimately, the findings of this research can inform targeted interventions aimed at fostering more inclusive and equitable transportation systems that cater to the needs of all residents, regardless of their ethnic background.

Chapter 2: Literature Review

This chapter expands on the previous background introduction to explain the significance, motivation and related work of this study. This section is divided in four parts, including introduction and review of the major benefits of accessibility to public transport (2.1), scientific evidence of access inequality among demographic groups in global cities (2.2), London transport strategy that aims at sustainability, healthy transit mode and opportunities (2.3), some existing methods for examining demographic disparities in accessibility.

2.1 Benefits of Accessibility to Public Transport

Cities rely on transportation systems to function effectively, providing residents with access to essential urban services. Having good access to public transportation is important for a better quality of life in cities and directly impacts how satisfied people are with their urban experience (Saif, Zefreh and Torok, 2018). When it comes to urban transport accessibility, there are primarily two major ways of getting around: public transport and private cars. Accessibility is not only a vital aspect but also a significant metric in evaluating public transportation(Saif, Zefreh and Torok, 2018), it refers to the quality of transit offered within a specific area and how easily people can use that service (Verseckienė, Meškauskas and Batarlienė, 2016).

Transport accessibility equality ensures people's right to equitable access to opportunities and services. It fosters urban inclusivity, diminishes disparities among diverse groups concerning employment, education, income, and so on, ultimately enhancing urban well-being. Research indicates that individuals with lower incomes rely more heavily on public transport for their travel needs compared to those in higher-income groups (Rojas *et al.*, 2016). Therefore, enhancing public transport accessibility stands as the foremost concern for improving access equality to opportunities within cities. Public transport typically falls under the purview of the public sector, functioning as a fundamental urban public service facility. Consequently, it embodies traits like government oversight, prioritizing disadvantaged groups, and striving for spatial fairness. Investments in new public transport infrastructure are crucial for achieving shifts in transportation patterns, facilitating new urban developments, and providing access to employment, education, healthcare, and other essential services. Throughout this process, the public sector seeks to enhance social inclusion by ensuring equal participation opportunities for all neighbourhoods, thus contributing to the creation of a more inclusive society.

2.2 Access Inequality

2.2.1 Inequality of Accessibility Among Demographic Groups

In the context of urban accessibility disparities, academic research has predominantly concentrated on inequalities in job accessibility. The literature has examined accessibility inequality from various perspectives. In the megacity of São Paulo, Brazil, Slovic et al. (2019) discovered uneven urban accessibility, particularly in terms of job accessibility. They uncover the unequal spatial distribution of job accessibility and emphasize worse-off individuals as measured by socioeconomic status, life expectancy, MHDI experience longer commuting times, reduced levels of accessibility, and fewer social opportunities and inclusions (Slovic *et al.,* 2019). According to Dodson et al. (2011), accessibility in Australian cities varies based on socioeconomic status (SES) and spatial location. Their study employed clustering to focus on travel demand analyses for low-income disadvantaged groups. However, they did not provide a detailed capture of the statistical inequality among different income groups.

In addition to socioeconomic factors such as income and education, many scholars have discovered that accessibility by public transport is unequally distributed among different age groups and genders (Martínez and Santibáñez, 2015; Rojas *et al.,* 2016).

In dividing the study city into three categories from inner to outer zones using a circular structure, Smith et al. (2020) and Giannotti et al. (2021) examined accessibility-related inequality in terms of occupational class. Their findings revealed that inequality exists in London's public transport system, favouring professional employment groups situated in the city centre and more affluent segments who have an advantage in employment opportunities. Concerning ethnic inequalities in transport accessibility, researchers who have explored highly segregated cities such as Detroit and San Francisco have primarily focused on race and ethnicity (Kawabata and Shen, 2007; Grengs, 2012). Grengs' (2012) research, counterintuitively, suggests that ethnic minorities and low-income groups do not experience the traditional disadvantages in transport accessibility. Instead, they enjoy easier access to public transport due to their residence in city centres. However, residents of the city centre are hindered by limited car access and the constraints posed by insufficient public transport services and travel costs.

The distribution of urban demographics and accessibility can vary significantly from city to city, especially across countries and continents, owing to disparities in policies, cultures, and historical evolution. In certain cities, affluent groups reside in downtown areas characterised by higher land values and an abundance of services, as seen in São Paulo, Brazil (Slovic et al., 2019). Conversely, in other cities, factors like high crime rates and the trend of counter-urbanization can result in city centres being occupied by relatively less advantaged groups. This situation is evident in cities like London, United Kingdom (Giannotti et al., 2021), and Detroit, USA (Grengs, 2012).

2.2.2 New Investments in London: Bridging or Widening the Accessibility Gap?

In the past two years, Transport for London has introduced significant expansions to London's public transport network: the Northern Line Extension (NLE), the Elizabeth Line, and the London Overground extension to Barking Riverside. These projects have brought substantial capacity and connectivity advantages to the transport system, opening up substantial portions of London for new housing and job opportunities. The question arises: Are these new investments bridging or widening the accessibility gap?

Development of transport is to enhance the sustainability of urban mobility, improve spatial efficiency, and mitigate urban sprawl, numerous cities worldwide have embraced transit-oriented, high-density, mixed-use development patterns. These patterns integrate public transport stops within city-centre locations, aligning urban land use and reuse (Smith and Barros, 2021). London's current London Plan places emphasis on "active, efficient, and sustainable travel" in its transport strategy through "high-density mixed-use sustainable development with associated public transport investment" (Greater London Authority, 2018). However, Over the past decade, the availability of affordable homes in London has diminished due to the shifts in the socio-political and economic landscape.

The literature suggests that public transport investment often results in area upgrading and varying degrees of gentrification. Studies of the global cities such as Madrid, Beijing and Hongkong, suggest public transport development brings up housing prices near the stations (So, Tse and Ganesan, 1997; Yiu and Wong, 2005; Dorantes, Paez and Vassallo, 2011; Zhou *et al.*, 2022). And this pattern is normally in line with the development planning and land use policy (Zhou *et al.*, 2022). Taking a closer look at the new investment of certain stations or lines, the impact is more locally distributed (Padeiro, Louro and Da Costa, 2019).

Thus, when new public transport investments are made in areas where low-income groups settle, increased accessibility can lead to a new cycle of group replacement and ultimately gentrification. Hamnett (2003) examined evidence of gentrification-induced displacement in London, highlighting gentrification's significant role in reshaping inner London's social geography from the 1960s to recent decades.

Through the last decade, London has experienced an uplifting of house prices (Song *et al.,* 2019), where private landlords' involvement and population growth in the city centre have driven both high housing prices and rental prices. Low-income groups are increasingly restricted by the scarcity of social housing in expensive London areas, leading them to relocate to outer areas with poorer public transport accessibility (Smith and Barros, 2021), resulting in a remaining or even wider gap of access inequalities.

2.3 London's Transport Strategy for Equality

2.3.1 Contextualizing Opportunities in Policy

In the global climate change scenario, sustainable transportation emerges as a critical key to achieving the Sustainable Development Goals (SDGs). A United Nations report (United Nations, 2021) underscores how vulnerable demographics, including those with lower incomes, disabilities, elderly individuals, women, and young people, heavily rely on public transportation to meet their accessibility and mobility needs. Nations across the globe have committed to fostering public transport development, striving to construct it in a manner that ensures equitable access for diverse groups.

Public transport holds a promising future due to its low carbon emissions alignment with the UK Government's Net Zero Strategy. The Net Zero Strategy report reflects the government's dedication to decarbonize and enhance public transport, encompassing the integration of various modes like buses and railways to bolster connectivity (HM Government, 2021).

The London Mayor's Strategy outlines a target for London's public transport, as in figure 2.3.1: sustainable transit modes will comprise 80 percent of all transportation by 2040 (Mayor of London and Transport for London, 2022). Driven by this objective, London aims to create a more interconnected and accessible transport network, encouraging walking, and the usage of bicycle and public transport, while fostering an inclusive and equitable environment for accessing opportunities. Simultaneously, Opportunity Areas (OAs) are designated in the London Plan as zones with distinct development potential, playing a crucial role in delivering the additional 66,000 homes London requires each year. Therefore, OAs represent significant development zones for enhancing transport accessibility.

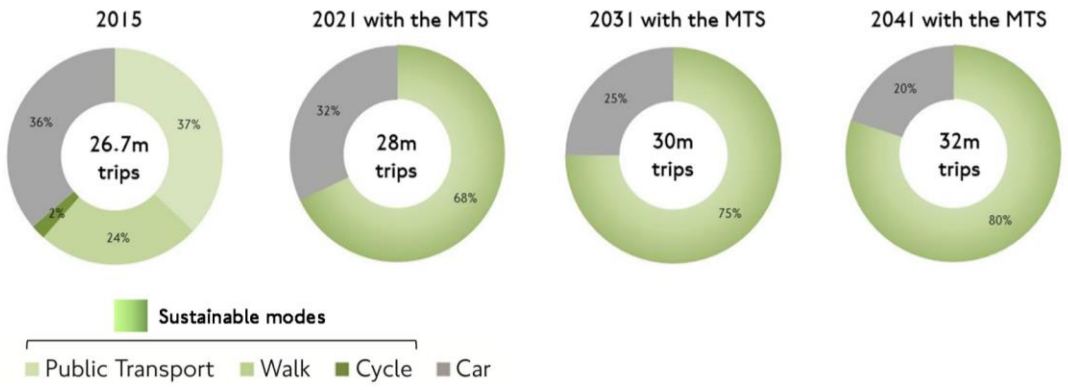


Figure 2.3.1. Transport scenario mode share (2015 – 2041) from London Mayor Transport Strategy (Mayor of London and Transport for London, 2017).

2.3.2 Open Data's Depth of Insights

Transport for London (TFL) possesses a notably extensive and open transport dataset. They have developed various transport models for London and a toolkit called WeCAT, which provides convenient access to the Public Transport Accessibility Levels (PTAL). PTAL is a method often used in London transport planning to evaluate the accessibility level of specific geographic areas to public transport. It measures how effectively a location is connected to public transport services (Transport for London and Mayor of London, 2015).

In recent years, the availability of the 2021 census data has also supported longitudinal population research. London's ethnicity data highlights the ongoing diversity in its composition, forming the basis for studies on ethnic distribution.

2.4 Methods for Analysing Demographic Disparities in Accessibility

Accessibility studies often employ modelling techniques to quantify transport demand, traffic volumes, and accessibility levels. Among these, the evaluation of transport accessibility has been an evolving topic of discussion. Scholars have developed various methodologies to measure accessibility. Geurs, De Montis and Reggiani (2015) classify accessibility calculations into four groups: infrastructure-based (evaluating proximity to facilities), person-based, utility-based (incorporating individual preferences, travel behaviour, and mode choices), and place-based or location-based (considering amenities within travel time from a point; and utility-based measures).

In recent years, more researchers have started implementing newly developed accessibility measurement techniques such as OpenTripPlanner (Duncan, 2020) and programming packages like r5r (Pereira *et al.*, 2021). However, despite this progress, the cumulative measure remains the most common approach among scholars when examining accessibility. This approach, which belongs to the location-based method as mention above, involves calculating the number of reachable jobs within different travel times and subsequently comparing and analysing them. However, there are fewer studies using infrastructure-based assessment.

Some literatures have focused on extracting specific groups and stratifying accessibility across different transportation modes, drawing conclusions from descriptive statistics (Kawabata, 2009; Smith *et al.*, 2020). However, these studies are limited in that they only visually represent the accessibility disparity among occupational groups as indicated by the data.

When quantitative studies delve into spatial analysis, the issue of spatial independence becomes a critical consideration. Firstly, the local impact of transport stations was addressed in Padeiro, Louro and Da Costa's study (2019). Secondly, the serious issue of spatial mismatch in regression models was mentioned in Kawabata's spatiotemporal analysis of transport accessibility (Kawabata, 2009). In this case, although Slovic et al. (2019) calculated spatial local autocorrelation when overlaying accessibility and inequality factors to showcase spatial segregation in the city using the Human Development Index, there is a lack of statistical modelling to tackle this concern. In Chen et al.'s (2019) study on spatial variations in hospital accessibility, the authors employed a spatial lag model to address the spatial autocorrelation issue in the regression model and confirmed the optimization effect of this model adjustment.

Incorporating temporal factors into this spatial analysis, (Kawabata and Shen, 2007) utilized a spatial regression model to analyse time differences in daily commuting by car and public transport for various ethnic and occupational groups in San Francisco. By considering two different years (1990 and 2000), they discovered that shorter commute times are significantly associated with improved job accessibility, with public transport being more relevant than cars in this regard. The spatial model exhibited better overall performance compared to the ordinary least squares (OLS) model.

In terms of the feature extraction of population, existing studies have explored disparities in accessibility, particularly focusing on disadvantaged groups defined by characteristics like income, race, or car ownership (Martens, Singer and Cohen-Zada, 2022). Fewer studies have focused on ethnicity and age, especially in London.

Chapter 3: Methodology

This chapter introduces the methodology of this paper based on the review and summary of the literature in chapter 2, including three aspects: 3.1 study area, 3.2 data, 3.3 Methodology Overview. the study area part introduces the spatial scope and spatial units of concern of the study, the data includes Access Index (from PTAL); Neighbourhood demographics; Geographical factors; Potential confounders; Methodology includes spatial dependence analysis, model selection, spatial regression models, and spatial dependence analysis. The methodology includes spatial dependence analysis, model selection, spatial regression models, and model evaluation.

3.1 Study Area

3.1.1 Study Boundary

This study analyses public transport accessibility and demographic characteristics in terms of spatial distribution within the Greater London Area (GLA). Within the GLA, the tube and buses are the most commonly used means of transport by city dwellers to commute within the city, radiating outward from the city's central area.

3.1.2 Spatial Unit

This paper uses the second smallest unit of the census, known as Lower Layer Super Output Areas (LSOAs), which consist of between 400 and 1,200 households or 1,000 to 3,000 individuals. New LSOAs have been established in 2021 census through the merging or division of the 2011 LSOAs due to changes in population (Office for National Statistics, 2021). To ensure consistency, this paper converts the 4994 LSOAs in the 2021 census back to the 4835 LSOAs in 2011.

3.2 Data

To maintain interpretability, this study refrained from applying any transformations to the data. In order to make comparisons across years and different regression models, the demographic features (section 3.2.2) are divided into five quintiles based on a 20% percentage split.

3.2.1 Accessibility

This study use Access Index which was extracted from the Public Transport Accessibility Levels (PTAL) dataset (2010 and 2023) from Transport for London (TFL). Each area is given a PTAL level score that ranges from 0 (very poor access) to 6b (excellent access) based on an underlying Access Index (AI) value, which is continuous measure ranging from 0 to over 100. Here, instead of using PTAL categories, we chose the continuous AI value as our measurement of accessibility of public transportation in Greater London Area. The calculation is based on the service access points and transportation route and service frequency. Below is a summary of formulas from the TFL connectivity guide (Transport for London and Mayor of London, 2015).

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

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

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

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

This study computed an average AI value for each LSOA based on the original 5m grid published by TFL, in order to combine with other demographic variables. By merging the datasets for 2010 and 2023, covering a span of 12 years, the change of data shows (1) the opening of new stations or the closure of old ones, and (2) the increase or decrease in the frequency of public transport services in terms of overall accessibility.

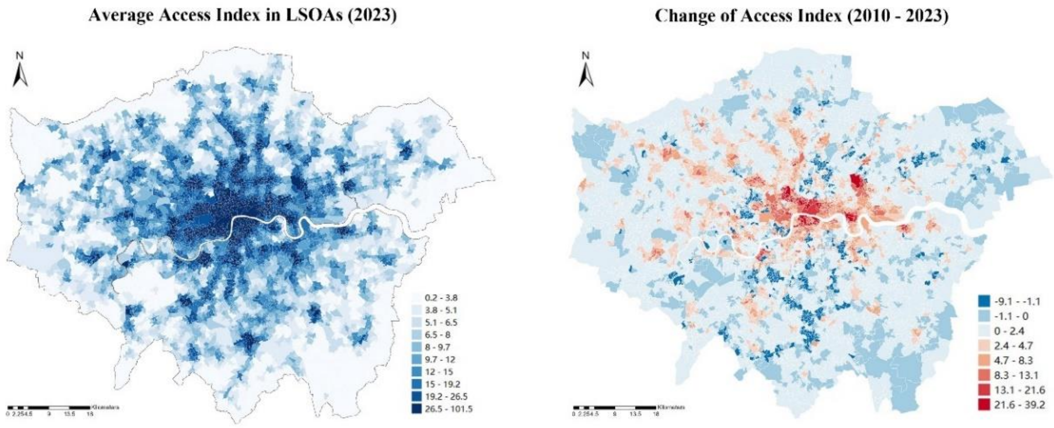


Figure 3.2.1. Spatial distribution of average Access Index at the LSOA level across Greater London Area for 2023; Spatial distribution of change of Access Index from 2010 to 2023 (data source: TFL).

In Figure 2, the access Index shows a decline in some areas due to a number of bus routes, stops and frequency of departures being downgraded or even temporarily cancelled from the start of the 2020 Covid outbreak. Many services have not been fully restored to their original levels until early 2023, when the data is calculated.

3.2.2 Neighbourhood demographics

Ethnicity

Race and ethnicity are from UK census data in 2011 and 2021 (Office for National Statistics, 2022). This study extract LSOAs within GLA and divided 19 types of ethnicity into 5 categories based on the classification of UK government and ethnicity question of The Office for National Statistics (GOV.UK, 2021), and calculate the percentage of each ethnic group within LSOAs. The ethnicity category used in this study is:

- Asian: Bangladeshi, Chinese, Indian, Pakistani, Other Asian;
- Black: African, Caribbean, Other Black;
- Mixed: White and Black Caribbean, White and Black African, White and Asian, Other Mixed;

- White: English/Welsh/Scottish/Northern Irish/British, Irish, Gypsy or Irish Traveller, Roma (only 2021), Other White;

- Other: Arab, Any other ethnic group

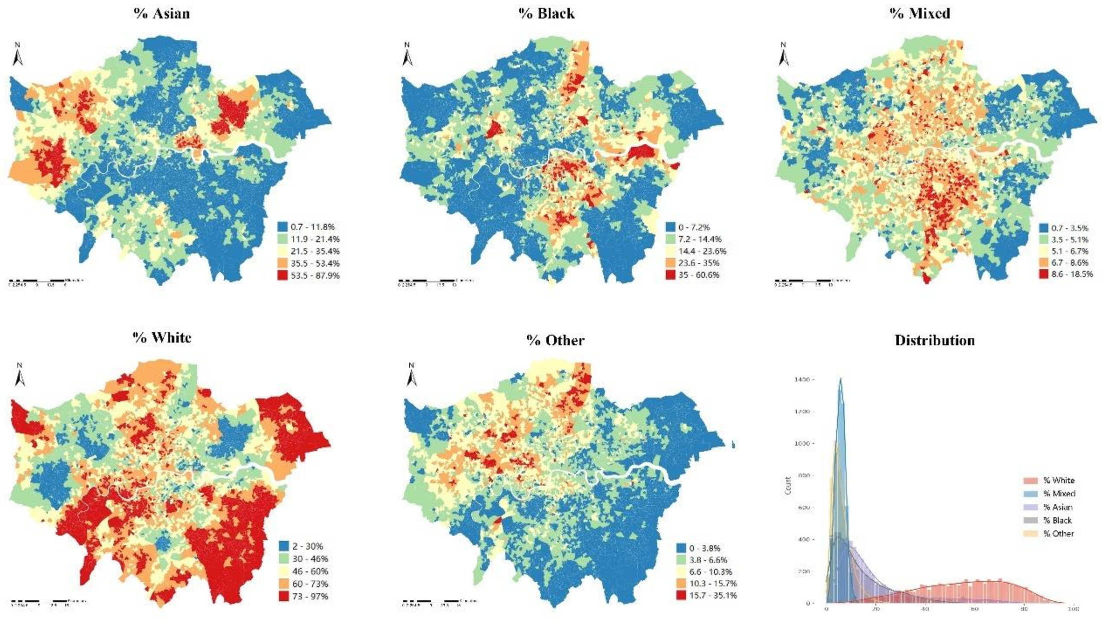


Figure 1.2.2. Spatial distribution of percentages for Asian, Black, Mixed, White, and Other ethnic groups at the LSOA level in 2021. Colour classes have been determined by Fisher-Jenks natural breaks.

Income

To research on different income groups, this study use the rank of income domain in the Index of Multiple Deprivation dataset in 2010 and 2019 (GOV.UK, 2011) (GOV.UK, 2019), and divided London LSOAs into 5 quantiles to represent low (Q1), median low (Q2), median (Q3), median high (Q4) and high income groups (Q4) (Klompmaker *et al.*, 2023).

Age

The age data is also obtained from the census data in terms of LSOA (Office for National Statistics, 2023a). In this study, the LSOAs are sorted by age according to the median age, and the mean age is compared if the median value is the same. In this way, the LSOAs are classified into five quintiles based on aging, ranging from the lowest to the highest: Q1, Q2, Q3, Q4, and Q5, respectively.

3.2.3 Geographical Factors

Opportunity Areas (OA)

Opportunity Areas are significant sites with development potential for new housing, commercial and infrastructure development, which are connected to existing or potential public transport improvements (Greater London Authority, 2021). There are 47 OAs identified by the London Plan including “adopted”, “emerging”, and “boundary to be define” types. This study uses the adopted boundary of OA and extracts LSOAs that intersect with boundary, defining them as "LSOAs benefited by OA."

Inner or Outer London

In academic research on transport accessibility studies, single-centre cities are often studied in different circles from inside to outside. For example, (Kawabata, 2009) divided Boston and San Francisco into "central city, inner suburbs and outer suburbs" to make comparison between these three regions. The study by (Smith *et al.*, 2020) (Smith and Barros, 2021) divides London Metropolitan Region into "inner Greater London Area (GLA), outer GLA and outer metropolitan area", in order to take into account all the traffic volumes and demands of daily commuters travelling in and out of London.

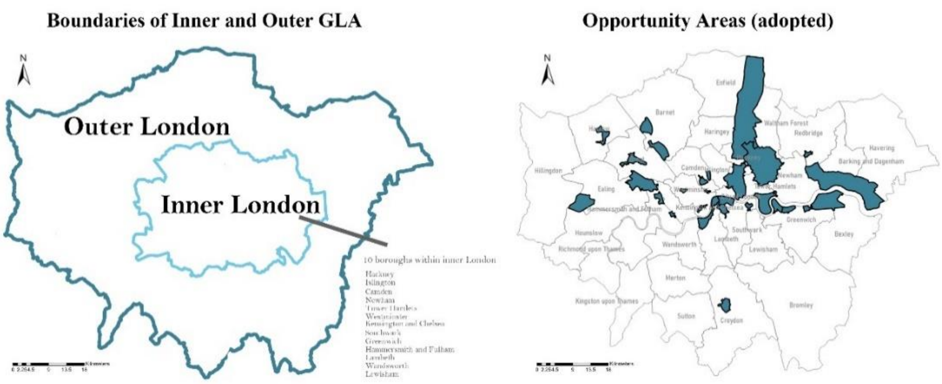


Figure 3.2.3. Boundaries of inner London, outer London of Greater London Area (GLA); Opportunity Areas (adopted ones).

Based on these ideas, this paper divides the GLA into Inner London and Outer London to provide an in-depth comparison to capture transit needs of daily commuters travelling within London.

3.2.4 potential confounders

Population density

Some literatures found a significant correlation between density distribution and accessibility (Gultom *et al.*, 2022). In order to control for the effect of this factor in this study, the number of residents counted in the census data was chosen to calculate the population density of each LSOA (Office for National Statistics, 2022).

Car ownership

Car ownership has been identified as a significant factor influencing the demand for public transport (Holmgren, 2007). On the other hand, research has also shown that affordable and sufficient public transport can deter car ownership (Cullinane, 2002). Temporal analysis reveals a complex interrelationship between the two (Holmgren, 2020). In London, data from the London Travel Demand Survey (LTDS) for the years 2005 to 2011 indicates that people living in areas further from public transport are more likely to own a car (Transport for London, no date).

In this context, if the model is constructed to consider only the relationship between ethnicity and public transport, the accessibility advantage enjoyed by car owners is overlooked. In other words, the fact that public transport accessibility is greater in the city center cannot be solely explained by demographic features such as ethnicity and income. Thus, car ownership (percentage of households with car/van in LSOAs) is considered in this study as the confounding variable, extracted from the 2021 census LSOA housing data (Office for National Statistics, 2023b).

3.2.5 Data summary

Overall, this study divides the data to 2010s variables and 2020s variables for illustration and model construction.

Table 3.2.5. Statistics of continuous variables for both 2010s and 2020s. Values rounded to 2 figures. All variables are calculated at LSOA level (n = 4835).

Variable		Year	Description	Mean	S.D.	Min	Max
Access Index	Total	2010	Average access index at LSOA levels, divided by transport mode	11.39	9.82	0.10	88.74
	Tube			2.23	4.18	0.00	32.53
	Bus			7.62	5.36	0.02	44.77
	Rail			1.54	2.83	0.00	36.26
Access Index	Total	2023		13.24	11.65	0.18	101.51
	Tube			2.98	5.62	0.00	44.86
	Bus			8.24	5.18	0.04	44.64
	Rail			1.94	3.72	0.00	40.74
	Tram			0.08	0.51	0.00	7.27
% Asian		2011	Percentages of ethnic groups at LSOA levels, grouped by sub-categories	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
% White		2011		60.69	20.37	3.54	98.16
		2021		55.15	18.75	1.94	96.62
% Other		2011		3.38	2.82	0.00	36.56
		2021		6.25	3.99	0.00	35.14
Income Deprivation Score		2010	Income deprivation score, only meaningful when making rankings	0.19	0.11	0.01	0.58
		2019		0.14	0.08	0.01	0.44
Age		2011	Median age at LSOA level	34.33	5.01	17.00	57.00
		2021		36.45	4.84	17.00	62.00
Population Density		2011	Population per km2 at LSOA levels	9647.63	6652.18	115.89	93957.51
		2021		10002.34	6423.85	119.37	70389.81
Car Ownership		2011		59.96	18.52	13.75	97.32

2021	Percentage of vhousehold with one or above cars or vans	60.06	18.84	13.27	96.22

To provide a detailed result for each of the ethnic group and prevent omitting one of the whole ethnicity, this study divided each ethnic categories into five equal quintiles (from low to high: Q1, Q2,Q3,Q4,Q5), and created new values based on one-hot encoding. Thus, in the analysis models, every Q1s were removed as the reference group for other higher levels of groups.

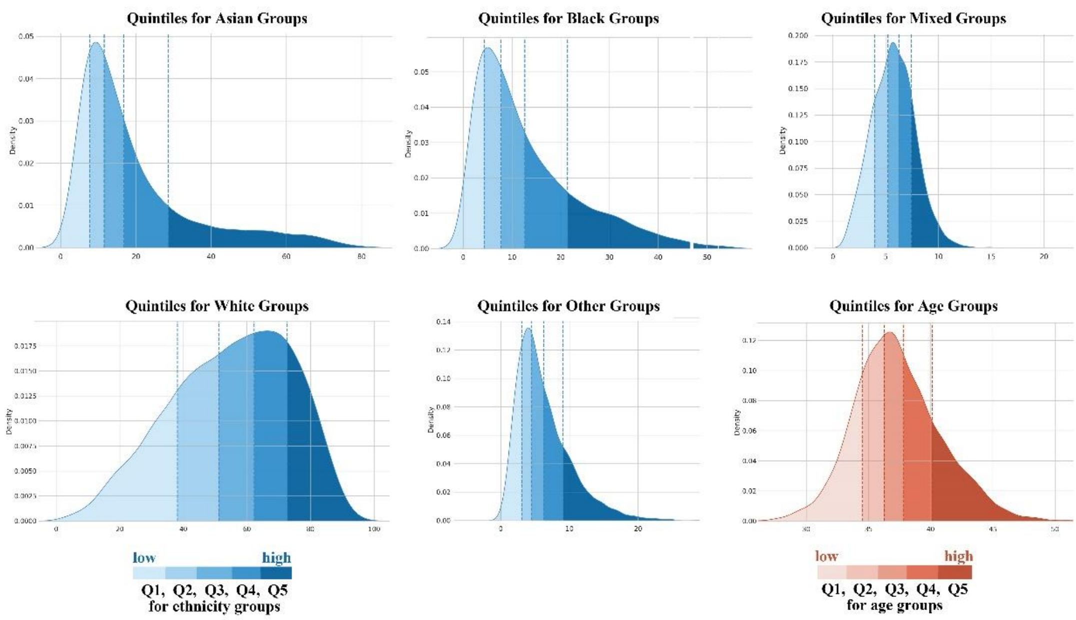


Figure 3.2.5. Distribution of quintiles of five ethnicity groups and age in 2021. All divided by equal percentages (data source: Census 2021).

3.3 Methodology Overview

Main goal of this study is to study at both cross-sectional associations and change. Specifically, our objectives were to estimate the associations between:

(i) 2011 LSOA level demographic characteristics and 2010 LSOA level Access Index;

(ii) 2021 LSOA level demographic characteristics and 2023 LSOA level Access Index;

(iii) LSOA level change in Access Index between 2023 and 2011 and 2011 LSOA level demographic characteristics.

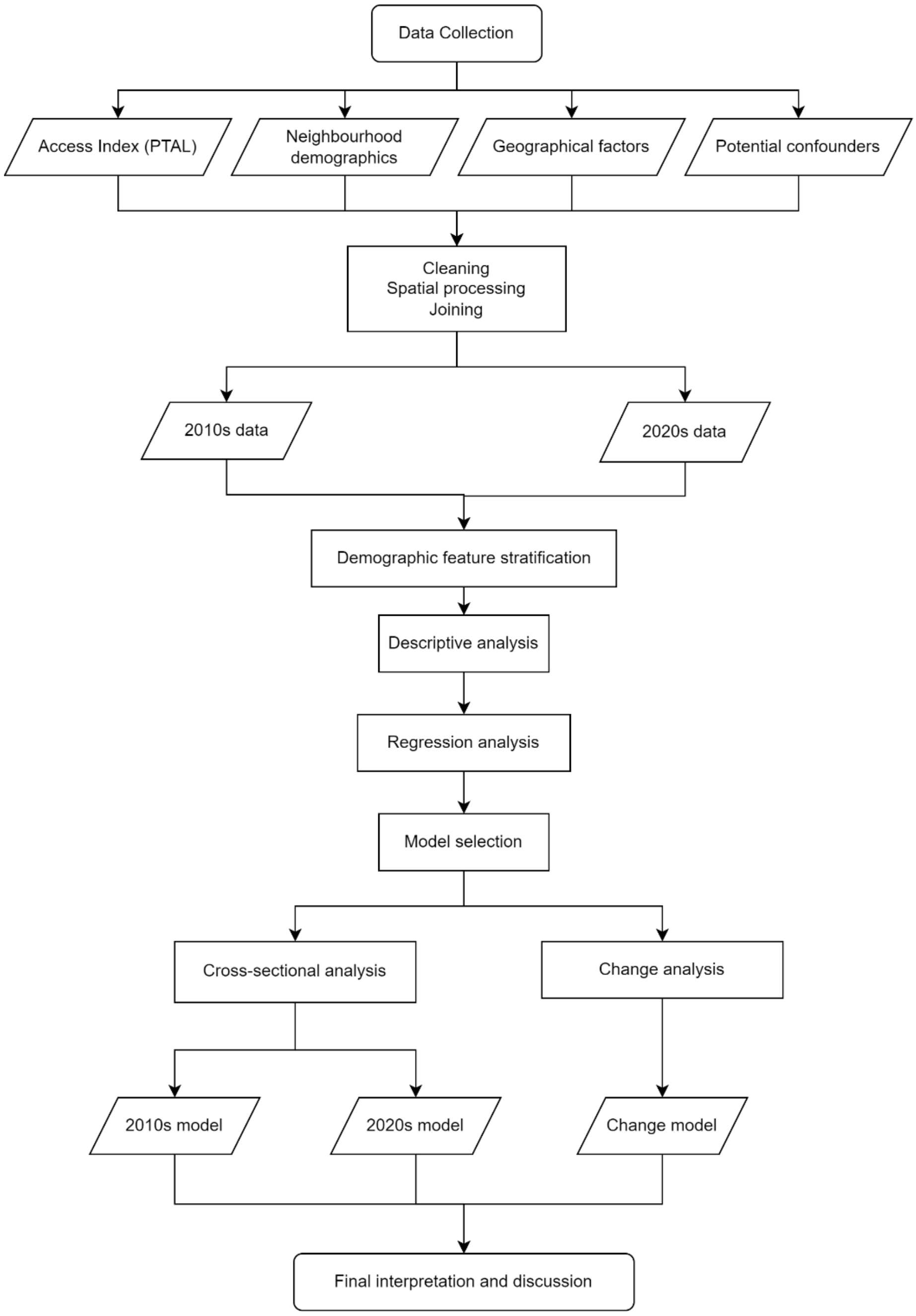


Figure 3.3. Workflow

3.3.1 Spatial dependence

It is reasonable to suspect that there is a high probability of spatial dependence due to the small size of the spatial unit LSOA used in this analysis, as well as the monocentric distribution of public transportation. LSOAs next to areas with stations or stops have higher chance of having greater accessibility, because the public transportation relies on continuous line connections. In other words, the public transport accessibility itself, as a response variable, may have an impact on the public transport accessibility of the surrounding area. Also, the possibility that the demographic features of the neighboring LSOAs have impact on a particular LSOA could not be excluded. Therefore, it is necessary to introduce appropriate spatial terms in regression models.

Before performing spatial regression, it is usually necessary to conduct a full spatial autocorrelation analysis on the dependent variable (Jiang, 2016). Spatial autocorrelation (Moran's I) serves as the primary method for analyzing spatial independence and measuring the degree of interdependence between the data at a given location and those in the surrounding area.

$$I = \frac{n}{\sum_i \sum_j W_{ij}} \frac{\sum_i \sum_j W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2} \tag{5}$$

In formula (5) (Moran, 1950), Y_i and Y_j represent the observed values of spatial units i and j, respectively. $\bar{Y}$ denotes the mean value of the observed Y values, n represents the number of spatial units, and W stands for the spatial weight matrix, typically subjected to row normalisation. The value of I falls within the range of [-1, 1]. A significant Moran's I indicates the presence of spatial autocorrelation (Moran, 1950).

3.3.2 Model selection

The significance of Moran’s I does not determine whether a spatial lag model or a spatial error model should be chosen. The empirical analysis process proposed by Anselin et al. (1996) serves as the most commonly used basis for model selection. The overall process is as follows: starting with the OLS regression, followed by the

Lagrange multiplier (LM) test and the robust LM test for the residuals, and then making a decision to use either the spatial error model or the spatial lag model based on whether and which test is significant.

3.3.3 Spatial regression analysis

After the test mentioned above, the initial step in spatial regression involves building the weighted matrix. Given the irregular shape of the London LSOAs, some of the common approaches such as rook or queen rules of selecting spatial neighbors are not meaningful. Therefore, this study chose k nearest neighbors (KNN) and selected the 8 closest neighbors in weighted matrix, to capture the local impact of accessibility (Padeiro, Louro and Da Costa, 2019).

Spatial Lag model (SLM)

$$Y_i = \alpha + \rho \sum_j \omega_{ij} Y_i + \beta X_i + \epsilon_i \qquad (6)$$

In formula (6), Y_i represents average Access Index value for each LSOA i. All the independent variables are included in X. The spatial weighted matrix ω_{ij}, based on the k nearest neighbours, captures the impact of Access Index in LSOA i on the neighbouring LSOA j. The symbol ρ denotes the parameter to be estimated for the spatial lag term of the dependent variable, which is also known as the spatial autoregressive coefficient.

Spatial Error Model (SEM)

$$Y_i = \alpha + \beta X_i + \epsilon_i$$

$$\epsilon_i = \lambda \sum_j \omega_{ij} \epsilon_i + \mu_i \qquad (7)$$

In formula (7), λ represents the coefficient to be estimated for the spatial autocorrelation error term, which is also known as the spatial autocorrelation coefficient. μ_i denotes the error term. The spatial weighted matrix ω_{ij} is based on the k nearest neighbors, capturing the impact of the error in LSOA i on the neighboring LSOA j. α donates as the constant term, while β stands for the parameter to be estimated, and ϵ_i represents the random error term.

3.3.4 Model Evaluation

In addition to the R-squared and adjusted R-squared, which reflect the overall explanatory power of the fitted model, this study employs three statistics proposed by Anselin (1988) for comparing the performance of spatial models:

- Log Likelihood;
- Akaike Information Criterion (AIC);
- Schwarz Criterion.

Among these, a larger value of the Log Likelihood statistic indicates a better model fit, whereas smaller values of the AIC and Schwarz Criterion statistics indicate better model fit. It's noticeable that the value of R^2 and adjusted R^2 should not be directly compared between OLS model and the spatial lag model as they differ in fit goodness (Anselin, 1988).

Chapter 4: Result

This chapter uses the data and methods introduced in Chapter 3 to present the results of both descriptive and quantitative analyses. The results consist of three main parts: 4.1 Descriptive Results. This part demonstrates the initial bivariate analysis as a starting point; 4.2 Cross-sectional Results. This part is subdivided into 4.2.1 Spatial Independence and Regression Model Selection, and 4.2.2 Analysis of Regression Results; 4.3 Change Data Analysis. This section explores the relationship between changes in accessibility values from 2010 to 2023 and the base-year (2011) demographic characteristics.

Section 4.2 aims to showcase research objectives (1) and (2), while Section 4.3 aims to address research objective (3) as mentioned in Chapter 3.3.

4.1 Descriptive analysis

This study begins with a bivariate analysis of the main focus: ethnicity and accessibility, without considering other variables.

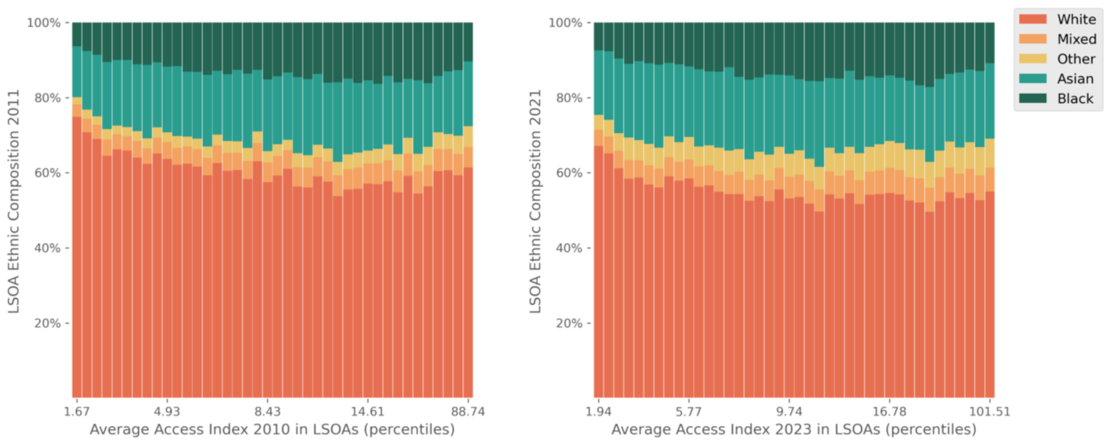


Figure 4.1. Average ethnicity composition by levels of Average Access Index in LSOAs (n = 4,835) in Greater London Area. The x-axis of each plot was divided by 2.5 percentile.

The Figure 4.1 shows that in both 2011 and 2021, the White group has the largest share among all races, with a concentration between 50% and 60%. This is followed by the Asian group, and then the Black group. Comparing the two years, the White racial share declines, while the mixed and other groups, as well as the Asian group, increase; the Black share does not change significantly. Intuitively looking at the figures, from left to right, the higher the accessibility, the lower the proportion of the White groups, while the proportion of the Black group increases slightly. The Asian group, the other group, and the mixed group increase in proportion as accessibility improves, but not significantly. This is due to the fact that the White group is more distributed in the suburban areas of outer London, in line with the distribution of the higher-income, car-owning groups while the public transport is mostly gathered in the centre areas. Therefore, we need to control for this type of potential covariant when analysing accessibility and ethnicity shares.

4.2 Cross-sectional analysis

4.2.1 Spatial dependence and model selection

In this study, the construction of the OLS model is used as a starting point to perform Moran's I test on the residuals of the dependent variable in the model, revealing the degree of spatial autocorrelation existing in the variables. The Lagrange multiplier (LM) test and the robust LM test are also conducted on the OLS model to select the appropriate spatial regression model based on the significance of the test results.

Table 4.2.1. Result of Moran's I, LM test, Robust LM test for OLS models; Statistic result for spatial regression models. All models were built with the Total Access Index as the response variable, and demographic characteristics and potential confounders as independent variables.

	OLS (2011)	OLS (2021)	LAG (2011)	LAG (2021)	ERROR (2011)	ERROR (2021)
Moran's I	0.474	0.567	0.121	0.161	0.643	0.720
P value	0.001	0.001	0.001	0.001	0.001	0.001
Log likelihood	-15793	-16596	-13941	-14140	-13985	-14118
Akaike info criterion (AIC)	31651	33256	27948	28346	28033	28299
Schwarz criterion	31858	33463	28161	28560	28241	28507
LM-Lag	4364 ***	5783 ***				
Robust LM-Lag	465 ***	397 ***				
LM-Error	4663 ***	6674 ***				
Robust LM-Error	764 ***	1288 ***				

The test results illustrate that the original OLS model exhibits significant spatial autocorrelation (significantly with 0.474 and 0.567). Therefore, spatial regression was selected in this study to capture the spatial effects and optimise the model's performance. The results of the LM test indicated significance for both the LM lag and the LM error tests, while in the further investigation with the Robust LM test, the results also show significance for both the lag and error terms, suggesting the potential impact of both on spatial independence. Consequently, this study constructed both models for comparison.

Comparing the Moran's I of the different regression models, it can be concluded that: (1) Only the Spatial Lag models reduces the degree of spatial autocorrelation in the original OLS model, while the Spatial Error model increased this problem. (2) When compared with the Spatial Error model, the Spatial Lag model exhibits the smallest Moran's I value, essentially overcoming the issue of spatial autocorrelation. Referring to Table 4.2.1, the LM lag value is larger than the LM error value in the LM test results, which further confirms that the spatial lag term has a greater impact on this model.

Additionally, the three metrics proposed by Anselin (1988) – Log Likelihood (lower), AIC and Schwarz Criterion (higher) – all satisfy the criteria for model optimisation. This further validates that the spatial model is better tuned to the spatial global autocorrelation problem. Combined with theoretical analyses for the spatial distribution of public transit in Chapter 3.3.1, the spatial lag model is chosen for subsequent regression analyses in this study.

4.2.2 Results of spatial regression

Cross-sectional analysis

The spatial lag models for both 2011 and 2021 are significant, indicating inequalities in access to public transit by ethnicity, income and age after accounting for population density, car ownership, the LSOA's location (inner or outer London, within or out of Opportunity Areas).

The total explained amount of the spatial lag model for 2011 is 0.83, with the spatial lag term "Weighted Access Index" contributing 27% to the explained amount. This indicates that spatial autocorrelation has a strong influence on the model of this study. Similarly, in the model of 2021, the spatial lag term contributes 35% to the total explanation of the model, which was 87%.

All Q1s were removed due to the principle of one-hot encoding. Additionally, in this study, the VIF was set to 5 to test multicollinearity, thus the white group Q5 was also removed.

Table 4.2.2. Result of spatial lag regression between total Access Index 2023 and 2021 demographic variables, adjusting for geographical features, potential confounders, and spatial lag autocorrelation term. Q1s were all removed as reference groups. Figures in the cells were regression coefficients in 2011, the results for 2021 were in the brackets.

Demographic features	Q1	Q2	Q3	Q4	Q5
Race/ethnicity					
% White	ref	-0.294 . (-0.026)	-0.112 . (0.278)	-0.262 . (-0.056)	/
% Mixed	ref	-0.537 ** (-0.371)	-0.873 *** (-0.583 **)	-0.807 *** (-0.521 *)	-0.865 *** (-0.914 ***)
% Asian	ref	0.479 * (0.273 .)	0.594 ** (0.725 ***)	1.113 *** (1.143 ***)	1.376 *** (1.220 ***)
% Black	ref	0.483 * (0.262 .)	-0.105 . (-0.423 .)	-0.089 . (-0.259 .)	-0.508 . (0.001 .)
% Other	ref	-0.430 * (-0.831 ***)	-0.491 * (-0.888 ***)	-0.693 ** (-0.907 ***)	0.911 *** (-1.321 ***)
Income	ref	1.496 *** (0.630 **)	2.365 *** (1.047 ***)	3.079 *** (1.693 ***)	3.651 *** (1.675 ***)
Age	ref	0.339 . (0.210 .)	0.619 ** (0.178 .)	0.526 * (0.022 .)	0.596 * (0.323 .)
Geographical features	0 (outside)	1 (inside)			
Opportunity area (within)	ref	0.256 . (-0.093 .)			
Outer London	1.423 *** (1.713 ***)	ref			
Adjusted variables					
Weighted	0.846 ***				

Access Index	(0.891 ***)
Population density (persons/km^2)	-0.00006 *** (-0.00006 ***)
Car ownership	-0.194 *** (-0.170 ***)
Model summary	
adjusted R2	0.83 (0.87)
p value	0.000 (0.000)

Note: Figures in the cells were regression coefficients in 2011, the results for 2021 were in the brackets. *** stands for statistical significance at a very strong level($p < 0.001$); ** stands for statistical significance at a strong level ($p < 0.01$); * stands for statistical significance ($p < 0.05$); . stands for weak statistical significance ($p < 0.1$).

a) The Association between Ethnicity and Accessibility

In this study, the total access index, Bus Access Index, and Tube Access Index are used as independent variables to construct the spatial lag model. The model's variables include neighbourhood characteristics (ethnicity, income, and age) and adjusted features (including population density, car ownership, and location). The ethnic groups are divided into five quintiles based on the level of percentage in LSOAs, including Q1 (low level), Q2 (median low level), Q3 (median level), Q4 (median high level), Q5 (high level). The coefficients in the result are only comparable to the reference Q1 level. This study compares between the relative relationships of ethnic group levels and the reference level to interpret the temporal differences.

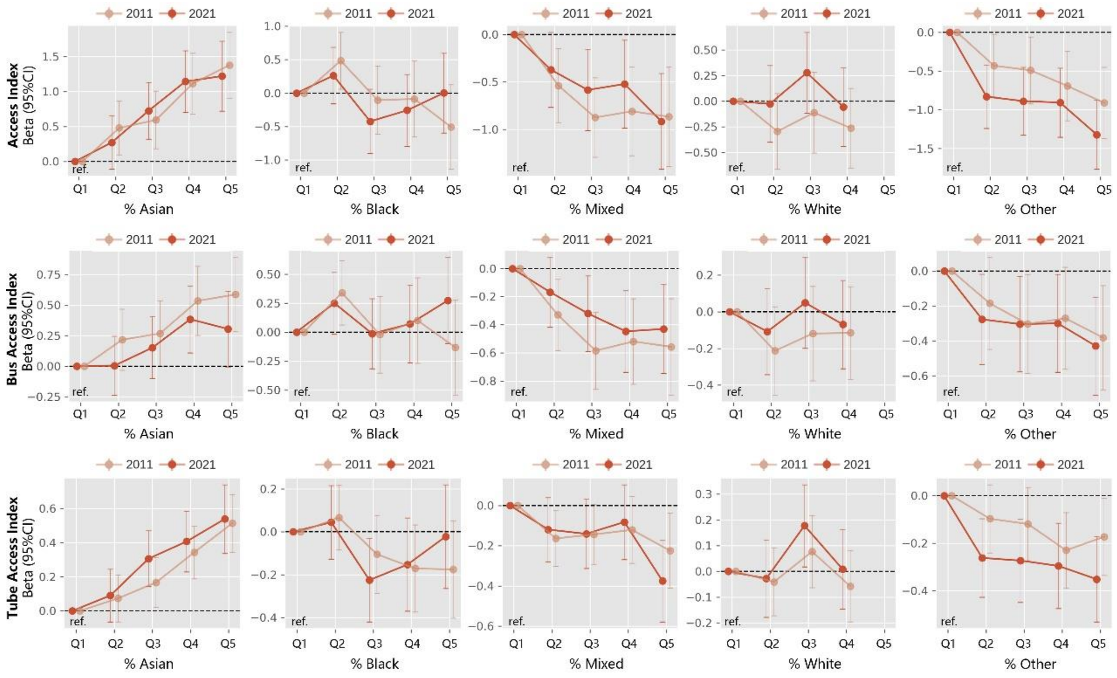


Figure 4.2.2.1. Associations of total Access Index, bus Access Index, tube Access Index in 2010 and 2023 and five quintiles of percentages of ethnic groups at LSOA level in 2011 and 2021 respectively. Percentages rose from Q1 to Q5. All coefficients were within the 95% Confidence Interval. Q1s were all removed as reference groups.

The relationship between each of the five ethnic groups and public transit accessibility varies. While in terms of different transit modes, different levels of ethnic groups demonstrate similar trends of correlation. Specifically, the Asian groups show a consistently significant positive correlation with total public transit access index, indicating the advantaged situation of Asian groups in the spatial distribution of accessibility. Notably, the total accessibility advantage becomes more pronounced as the percentage of Asian groups increases (from Q1 to Q5, with Asian% gradually rising). The LSOAs with the highest percentage of Asian groups have about 1.5 units of access index higher than the LSOAs with the lowest percentage (Q1, the reference group). A comparison between 2011 and 2021 reveals a slight reduction in the dominance of Asian groups in median low (Q2) and hight (Q5) LSOAs. Delving into the breakdown of transport modes, the correlation trend of Asian group is similar for bus and tube, ranging simultaneously from 0 to nearly 0.6. The decline in this advantage in bus accessibility for the Asian race from 2011 to 2021 is evident across all levels. Notably, the high-level (Q5) Asian share of LSOAs experiences the most significant decline in the bus accessibility advantage. This could due to (1) reduced bus service levels, and (2) significant migration within these areas.

On the other hand, the Black group presents a more complex scenario. Firstly, areas with median-low (Q2) values experience a public transport accessibility advantage in both 2011 and 2021, despite a declining one. Secondly, the negative correlations seen in Q3 and Q4 levels are mainly a result of the Black group's tube accessibility disadvantage (all negatively correlated). This disadvantage continues to grow from 2011 to 2021 in Q3. However, in the Q5 level with the highest proportion of Black residents, the enhancements in bus accessibility and tube accessibility are both notable, from -0.1 to 0.25 and -0.2 to 0 respectively. Consequently, in the overall Access Index, the Q5 segment of the Black group reflects a trend of greater benefit. However, this trend of inequality reduction does not extend to other levels of areas.

Counter-intuitively, white groups, often considered advantaged, do not possess an absolute advantage in terms of accessibility to public transport. This is demonstrated by both the total access index and the transit mode breakdown, revealing that only the median level (Q3) LSOAs hold a distinct advantage in public transport accessibility while other levels (Q2 and Q4) experience non-clear or slightly negative relationships. The correlations in 2011 got improved through the ten years.

Finally, the mixed group and the other group are examined together, considering that both have experienced disadvantages over the past decade. In terms of the mixed group, the disadvantage situation in bus accessibility has enhanced between 2011 and 2021, with all levels of districts showing less shortage. However, in the LSOAs with the highest share of the mixed group (Q5), tube accessibility has become significantly more disadvantaged, and the gap with other levels of districts further widens. In terms of other groups, unfortunately, as tube accessibility worsens significantly at all levels while bus accessibility remains more or less the same, the entire group become more disadvantaged in terms of total accessibility.

When comparing among all the ethnic groups, only Asian groups and some levels of black (Q2) and white (Q3) are advantaged with regard to the total accessibility. From 2011 to 2021, tube accessibility shows improvement in all level Asian, white and black areas, except for Q4 black level. Instead, dramatic declines happen in all areas across the other groups and Q5 level. In terms of the bus access index, both Asian, black and white groups have advantages, while this advantage declines in Asian groups and increases in white groups.

b) The Association between Income and Accessibility

Similar to the breakdown of ethnicity, this study also divides the LSOAs into five quintiles based on the income deprivation ranking. The most deprived LSOAs are categorised into Q1, representing the lowest income group. Other groups are median low groups (Q2), median groups (Q3), median high (Q4), high (Q5).

In the spatial lag model, the association between income level and accessibility is significant at all levels. There is a positive correlation between income and the total access index, and the higher the income level, the more clearly the advantage of accessibility is reflected. The LSOAs with the highest income (Q5) exhibits nearly four units of higher accessibility compared to the LSOAs with the lowest income (Q1, reference group) in 2011, however, this significant advantage dramatically went down through the decade (from 3.7 to 1.7), particularly for Q5, the highest income group, levelling to that of Q4 in 2021. The main contributor to the decline in the bus accessibility, where the highest income Q5 areas show a significant decrease (nearly drop to the half). Advantages for bus also drops for all income groups, with the approximately the same amount of decrease.

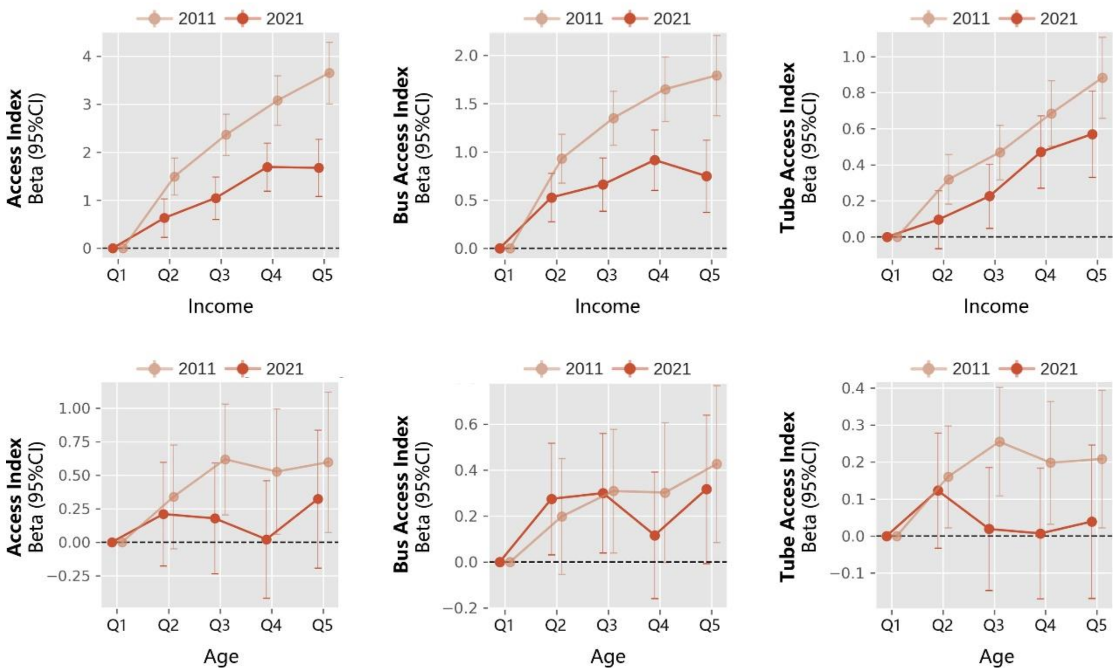


Figure 4.2.2.2. Associations of total Access Index, bus Access Index, tube Access Index in 2010 and 2023 and five quintiles of percentages of income and age groups at LSOA level in 2011 and 2021 respectively. Percentages rose from Q1 to Q5. All coefficients were within the 95% Confidence Interval.

c) The Association between Age and Accessibility

The result shows that the elderly groups are slightly benefiting from public transport accessibility but the median high aged groups do not have obvious advantage.

From 2011 to 2021, the advantage in tube accessibility went down on the aging groups (Q3, Q4 and Q5), leading to the decrease in the total correlation. The trend in bus accessibility is similar to the total value. Only groups in median low age (Q2) have gained more benefits in the past years. Overall, due to the small correlation coefficient between age level and accessibility (less than 0.5), accessibility does not play a strong role in the age distribution.

4.3 Change analysis

In order to quantify the relationship between changes in accessibility and demographic characteristics, this part uses spatial lag model to measure how demographic variables can account for changes in accessibility. Spatial lag models were constructed for the change in the total Access Index and base-year variables (2011) to investigate their relationship.

Table 4.3. Result of spatial lag regression between the change of Access Index from 2010 to2023 and 2011 demographic variables, adjusting for geographical features, potential confounders, and spatial lag autocorrelation term. Q1s were all removed as reference group.

Demographic features	Q1	Q2	Q3	Q4	Q5
Race/ethnicity					
% White	ref	0.038	0.126	-0.032	/
% Mixed	ref	-0.087	0.109	-0.107	-0.071
% Asian	ref	0.068	0.372 ***	0.322 **	0.462 ***
% Black	ref	-0.113	-0.167	-0.237	-0.180
% Other	ref	-0.123	-0.295 **	-0.168 **	-0.323 **
Income	ref	-0.200 *	-0.044	0.086	0.172
Age	ref	-0.172	-0.076	0.096	0.074
Geographical features	0 (outside)	1 (inside)			
Opportunity area (within)	ref	0.247 **			
Outer London	0.062	ref			
Adjusted variables					
Base year (Access Index 2010)	-0.023 ***				
Weighted change of Access Index	0.846 ***				
Population density (persons/km2)	0.000002				
% Car ownership	-0.032 ***				

Model summary	
adjusted R2	0.64
p value	0.000

Note: *** stands for statistical significance at a very strong level($p < 0.001$); ** stands for statistical significance at a strong level ($p < 0.01$); * stands for statistical significance ($p < 0.05$); . stands for weak statistical significance ($p < 0.1$).

Since the objectives of this study—public transport accessibility and demographic characteristics—are both changing during the decade from the 2010s to the 2020s, this study chooses to control for ethnicity distribution in this section. In this case, we assume that the population does not change between 2011 and 2021, and the public transport accessibility is the only variable that changes. Thus, we build a spatial lag model to measure the association between the change of the Access Index from 2010 to 2023 and the base year (2011) neighborhood demographics.

Similar to the cross-sectional model but more significant, the spatial lag term (weighted change of access) contributes to the overall model at 50%. This means that the change of the Access Index itself influences its own spatial changes more than all neighborhood features, geographic features, and neighborhood demographics combined. It explains almost twice as much of the model as all other factors. Consequently, many of the factors in the model are not significant, and their coefficients do not hold strong explanatory value.

Among all the variables, the significance of the factor related to Asian groups is more pronounced. There is more accessibility improvement in areas where Asian groups account for the median, median-high, and high levels (Q3, Q4, Q5), compared to the area with the fewest Asians, Q1. In the previous analyses, we found that in the base year, Asians have a significant advantage in accessibility, and this advantage strengthens as the percentage of Asians increases. However, the results presented in Table 4.3 show that the advantage of accessibility for areas with a large number of

Asians is further expanding. This advantage has the strongest correlation coefficient (0.462) other than the spatial autocorrelation coefficient for the LSOA with the highest level of Asian representation (Q5). Does this mean that public transport is investing further in areas that already have better accessibility? The answer is no. In the model, the effect of the base year's access index on the change in accessibility is significant, but the effect is negative. This implies that new investments in public transport are inclined to target areas that lack adequate accessibility. In this senario, the increase in dominance in areas with a high proportion of Asians can only be explained by the fact that new investment is still going to other areas with a high proportion of Asians, on top of the current dominance of Asians in public transport accessibility.

Another notable ethnic group is the one that stands in contrast to the Asian group. Additionally, other groups, which have faced significant disadvantages, also exhibit a negative correlation with accessibility enhancement. This implies that, instead of ameliorating the situation for these other ethnic groups, new public transport investments further solidify their disadvantaged positions, assuming there is no change in population distribution.

From a geographical perspective, the new public transport investment brings substantial benefits to LSOAs situated in the opportunity area. There is a 0.247-unit advantage in accessibility improvement for LSOAs within the OA, in comparison to those that are located outside it.

Another notable ethnic group is the other ethnic group, which stands in contrast to the Asian group. This group have faced significant disadvantages, and they experience a negative correlation with accessibility improvement. This implies that, under the assumption of an unchanged population distribution, new investments in public transport is potential to widen this existing negative disparity.

Regarding geographical impact, the new public transport investment brings significant advantages to LSOAs located within the opportunity area. These specific LSOAs witness a notable 0.247-unit improvement in accessibility, contrasting with LSOAs outside the opportunity area.

Chapter 5: Discussion and Conclusion

This work has managed to answer the questions: a) What are the relationships between public transport accessibility and demographic groups? and b) how does it change through the last decade, both in terms of ethnicity, income and age?

By extracting demographic features from the 2011 and 2021 census data at the GLA LSOA level, and collecting accessibility measurement indices from the 2010 and 2023 PTAL provided by TFL, two spatial lag models were constructed to conduct cross-sectional analyses for the 2010s and 2020s. And comparing to OLS model and spatial error model, spatial lag models in this study had better performances in reducing spatial dependence of accessibility. Additionally, another spatial lag model was developed to measure the association between the changes in accessibility and the 2011 demographic distribution. The cross-sectional models exhibited strong performance in terms of significance, total explained variation, and capturing spatial dependence. However, the absence of a coefficient of determination in the change model indicates the presence of more complex dynamics concerning change.

5.1 Research Summary

The results of this study revealed inequalities in access to public transportation by race/ethnicity, age and socioeconomic status after accounting for geographical features, car ownerships, population density and spatial autocorrelation. By comparing two years, this study also indicated temporal changes over the last ten years for different groups. These changes were further quantified in the change analysis. Although the contribution values and significance of the factors in the model were weak, they did reflect, to some extent, the propensity of transportation investment to OA and the inequality between the Asian and the other ethnic groups.

Specifically, this study found that neighbourhoods with higher populations of mixed and other ethnic groups had lower accessibility to public transport compared to neighbourhoods with higher percentages of Asian, black and white ethnic groups. Among these three more beneficial groups, Asian groups had higher accessibility for public transport at all levels, while the black groups and white groups did not gain complete advantages, with only neighbourhoods with median level populations showed more obvious priorities.

Both in 2011 and 2021, income also plays a role, showing wealthier groups tend to have better access to public transport. However, the positive relationship between income and accessibility had been found to decrease during the decade, especially for bus accessibility in the highest income level group.

Additionally, neighbourhoods with the highest percentages of aging group gained more benefits on overall accessibility and only for bus mode. Areas with more median low aged people had more advantages in both transport modes. The advantages of the elderly groups in public transport accessibility had diminished evidently through the years, especially for tube.

5.2 Limitations

- **The measurement of accessibility**

The accessibility measure we used for this study, which is also being employed by TfL for various planning stages, solely focuses on the distance to infrastructure, and it fails to consider travel time, ease of travel, and cost for different transportation options. This underscores the need for further research and improvement in this aspect. Additionally, the improvements brought about by new public transport investments have not been detailily measured. The impact of new transportation on accessibility extends beyond just stations and routes; it also includes the ease of transferring between various modes of transportation. Consequently, a comprehensive accessibility assessment must evaluate the effects of new transport investments within the framework of multiple modes of transportation.

- **The ethnic group has not been specifically targeted**

This study categorizes the population into five broad categories, leading to the problem of hidden differences and characteristics within these broad categories. The changes in the subdivided population within the broad categories are complex, and there are clear racial differences. Therefore, the categorisation at the time of the ethnicity study holds important implications for the study.

- **The dynamics of demographic migration have not been fully captured**

In fact, the relationship between demographic change and accessibility investment in terms of spatial distribution is very complex. Census data can only reflect increases or decreases in the proportion of people by ethnicity, and it is difficult to know the migration of the population.

- **Lack of analysis combined with individual transport demand**

Transport demand constitutes a vital determinant of travel modelling. This study analysed the characteristics of the population as a whole, using the area (LSOA) as a unit, thus, the specific characteristics and requirements of individuals are disregarded.

5.3 Future work

The context of public transport development represents London's long-term transportation policy direction. This paper employs spatial regression modelling and its results to offer a quantitative method for studying the extent and phenomenon of distributional inequalities in public transport accessibility across the population. The analysis can provide insights into optimising assessments of ethnic, income, and age equality within public transport advancement.

Groups facing accessibility disadvantages, including the mixed and other groups, as well as the black and white groups to some extent—underscored by the analysis results—point toward subjects meriting further research in the future. Moreover, the study's identification of Asian accessibility advantages calls for deeper investigation through racial and income stratification to uncover underlying rationales. The Mayor's Transport Strategy lays out the objective of enhancing equality and inclusivity in public transport. The outcomes of the analyses presented in this paper illustrate that average regional income levels stand as one of the obstacles to accessibility. This insight can shape forthcoming investments in public transport.

For the issue of capturing spatial dependence, this study tried the normally used SLM and SEM for comparison. However, in the future study, this might also be improved by adding more complex models such as Spatial Durbin Model, to improve the accuracy of the spatial relationships between the factors.

In conclusion, this research holds significant implications for policymakers in their practices to tackle disparities within public transport systems. By shedding light on the disparities of accessibility in ethnicity, age, income and accessibility, this study highlights the challenges faced by different demographic groups. This study can serve as a crucial tool for guiding policy decisions. Moreover, the insights from this research contribute to creating a more equitable and inclusive urban fabric, where public transportation is efficient and accessible to everyone. As cities continue to evolve, the outcomes of this study offer valuable insights that can shape policies aimed at fostering fairer urban environments and enhancing the overall quality of life for residents.

References

Anselin, L. (1988) ‘Model Selection in Spatial Econometric Models’, in Anselin, L., *Spatial Econometrics: Methods and Models*. Dordrecht: Springer Netherlands (Studies in Operational Regional Science), pp. 243–252. Available at: https://doi.org/10.1007/978-94-015-7799-1_14.

Aoun, C. (2013) ‘The smart city cornerstone: Urban efficiency’, *Schneider Electric White Paper*, 1, pp. 1–13.

Ceder, A. (Avi) (2021) ‘Urban mobility and public transport: future perspectives and review’, *International Journal of Urban Sciences*, 25(4), pp. 455–479. Available at: https://doi.org/10.1080/12265934.2020.1799846.

Chen, M. *et al.* (2019) ‘Spatial Difference of Transit-Based Accessibility to Hospitals by Regions Using Spatially Adjusted ANOVA’, *International Journal of Environmental Research and Public Health*, 16(11), p. 1923. Available at: https://doi.org/10.3390/ijerph16111923.

Cullinane, S. (2002) ‘The relationship between car ownership and public transport provision: a case study of Hong Kong’, *Transport Policy*, 9(1), pp. 29–39. Available at: https://doi.org/10.1016/S0967-070X(01)00028-2.

Dodson, J. *et al.* (2011) ‘How Will We Get There?: Analyzing Access of Low-Socioeconomic-Status Households to Destinations in Australian Cities’, *Transportation Research Record: Journal of the Transportation Research Board*, 2242(1), pp. 90–97. Available at: https://doi.org/10.3141/2242-11.

Dorantes, L.M., Paez, A. and Vassallo, J.M. (2011) ‘Analysis of House Prices to Assess Economic Impacts of New Public Transport Infrastructure: Madrid Metro Line 12’, *Transportation Research Record: Journal of the Transportation Research Board*, 2245(1), pp. 131–139. Available at: https://doi.org/10.3141/2245-16.

Geurs, K.T., De Montis, A. and Reggiani, A. (2015) ‘Recent advances and applications in accessibility modelling’, *Computers, Environment and Urban Systems*, 49, pp. 82–85. Available at: https://doi.org/10.1016/j.compenvurbsys.2014.09.003.

Giannotti, M. *et al.* (2021) ‘Inequalities in transit accessibility: Contributions from a comparative study between Global South and North metropolitan regions’, *Cities*, 109, p. 103016. Available at: https://doi.org/10.1016/j.cities.2020.103016.

GOV.UK (2011) ‘English indices of deprivation 2010’. Available at: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010.

GOV.UK (2019) ‘English indices of deprivation 2019’. Available at: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019.

GOV.UK (2021) ‘List of ethnic groups’. Available at: https://www.ethnicity-facts-figures.service.gov.uk/style-guide/ethnic-groups.

Greater London Authority (2018) *Mayor’s Transport Strategy*. Available at: https://www.london.gov.uk/sites/default/files/mayors-transport-strategy-2018.pdf.

Greater London Authority (2021) *The London Plan*. Available at: https://www.london.gov.uk/sites/default/files/the_london_plan_2021.pdf.

Grengs, J. (2012) ‘Equity and the social distribution of job accessibility in Detroit’, *Environment and Planning B: Planning and Design*, 39(5), pp. 785–800. Available at: https://doi.org/10.1068/b36097.

Gultom, B.J.B. *et al.* (2022) ‘FINDING THE CRAMPED SPACE IN A CITY: THE ACCESSIBILITY ASSESSMENT OF PONTIANAK CITY BASED ON THE GRIDDED POPULATION DENSITY’, *Jurnal Pengembangan Kota*, 10(1), pp. 47–56. Available at: https://doi.org/10.14710/jpk.10.1.47-56.

Hamnett, C. (2003) ‘Gentrification and the Middle-class Remaking of Inner London, 1961-2001’, *Urban Studies*, 40(12), pp. 2401–2426. Available at: https://doi.org/10.1080/0042098032000136138.

HM Goverment (2021) *Net Zero Strategy: Build Back Greener*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1033990/net-zero-strategy-beis.pdf.

Holmgren, J. (2007) ‘Meta-analysis of public transport demand’, *Transportation Research Part A: Policy and Practice*, 41(10), pp. 1021–1035. Available at: https://doi.org/10.1016/j.tra.2007.06.003.

Holmgren, J. (2020) ‘The effect of public transport quality on car ownership – A source of wider benefits?’, *Research in Transportation Economics*, 83, p. 100957. Available at: https://doi.org/10.1016/j.retrec.2020.100957.

Jiang, L. (2016) ‘The Choice of Spatial Econometric Models Reconsidered in Empirical Studies’, in. *Statistics & Information Forum*, pp. 10–16. Available at: https://doi.org/10.3969/j.issn.1007-3116.2016.10.002.

Kawabata, M. (2009) ‘Spatiotemporal Dimensions of Modal Accessibility Disparity in Boston and San Francisco’, *Environment and Planning A: Economy and Space*, 41(1), pp. 183–198. Available at: https://doi.org/10.1068/a4068.

Kawabata, M. and Shen, Q. (2007) ‘Commuting Inequality between Cars and Public Transit: The Case of the San Francisco Bay Area, 1990-2000’, *Urban Studies*, 44(9), pp. 1759–1780. Available at: https://doi.org/10.1080/00420980701426616.

Klompmaker, J.O. *et al.* (2023) ‘Racial, Ethnic, and Socioeconomic Disparities in Multiple Measures of Blue and Green Spaces in the United States’, *Environmental Health Perspectives*, 131(1), p. 017007. Available at: https://doi.org/10.1289/EHP11164.

Lagadic, M. (2019) ‘Along the London Overground: Transport Improvements, Gentrification, and Symbolic Ownership along London’s Trendiest Line’, *City & Community*, 18(3), pp. 1003–1027. Available at: https://doi.org/10.1111/cico.12414.

Martens, K., Singer, M.E. and Cohen-Zada, A.L. (2022) ‘Equity in Accessibility: Moving From Disparity to Insufficiency Analyses’, *Journal of the American Planning Association*, 88(4), pp. 479–494. Available at: https://doi.org/10.1080/01944363.2021.2016476.

Martínez, C.F. and Santibáñez, N.W. (2015) ‘Movilidad femenina en Santiago de Chile: reproducción de inequidades en la metrópolis, el barrio y el espacio público’, *urbe. Revista Brasileira de Gestão Urbana*, 7(1), pp. 48–61. Available at: https://doi.org/10.1590/2175-3369.007.001.AO03.

Mayor of London and Transport for London (2017) *Mayor’s Transport Strategy: Supporting Evidence (Outcomes Summary Report)*, pp. 1–82. Available at: https://content.tfl.gov.uk/mts-outcomes-summary-report.pdf.

Mayor of London and Transport for London (2022) *Delivering the Mayor’s Transport Strategy 2021/22*, pp. 1–78. Available at: https://content.tfl.gov.uk/tfl-mts-update-14-july-2022-acc.pdf.

Moran, P.A.P. (1950) ‘Notes on Continuous Stochastic Phenomena’, *Biometrika*, 37(1/2), p. 17. Available at: https://doi.org/10.2307/2332142.

Office for National Statistics (2021) ‘Census 2021 geographies’. Available at: https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/census2021geographies.

Office for National Statistics (2022) ‘Ethnic group, England and Wales: Census 2021’. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/ethnicity/bul letins/ethnicgroupenglandandwales/census2021.

Office for National Statistics (2023a) ‘Age variable: Census 2021’. Available at: https://www.ons.gov.uk/census/census2021dictionary/variablesbytopic/demographyvariablescensus2021/age.

Office for National Statistics (2023b) ‘Housing, England and Wales: Census 2021’. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/housingenglandandwales/census2021.

Padeiro, M., Louro, A. and Da Costa, N.M. (2019) ‘Transit-oriented development and gentrification: a systematic review’, *Transport Reviews*, 39(6), pp. 733–754. Available at: https://doi.org/10.1080/01441647.2019.1649316.

Pereira, R.H.M. *et al.* (2021) ‘r5r: Rapid Realistic Routing on Multimodal Transport Networks with R 5 in R’, *Findings* [Preprint]. Available at: https://doi.org/10.32866/001c.21262.

Rojas, C. *et al.* (2016) ‘Accessibility to urban green spaces in Chilean cities using adaptive thresholds’, *Journal of Transport Geography*, 57, pp. 227–240. Available at: https://doi.org/10.1016/j.jtrangeo.2016.10.012.

Saif, M.A., Zefreh, M.M. and Torok, A. (2018) ‘Public Transport Accessibility: A Literature Review’, *Periodica Polytechnica Transportation Engineering*, 47(1), pp. 36–43. Available at: https://doi.org/10.3311/PPtr.12072.

Serag El Din, H. *et al.* (2013) ‘Principles of urban quality of life for a neighborhood’, *HBRC Journal*, 9(1), pp. 86–92. Available at: https://doi.org/10.1016/j.hbrcj.2013.02.007.

Slovic, A.D. *et al.* (2019) ‘The long road to achieving equity: Job accessibility restrictions and overlapping inequalities in the city of São Paulo', *Journal of Transport Geography*, 78, pp. 181–193. Available at: https://doi.org/10.1016/j.jtrangeo.2019.06.003.

Smith, D.A. *et al.* (2020) 'A compact city for the wealthy? Employment accessibility inequalities between occupational classes in the London metropolitan region 2011', *Journal of Transport Geography*, 86, p. 102767. Available at: https://doi.org/10.1016/j.jtrangeo.2020.102767.

Smith, D.A. and Barros, J. (2021) 'Sustainable transport planning and residential segregation at the city scale', in *Urban Form and Accessibility*. Elsevier, pp. 27–44. Available at: https://doi.org/10.1016/B978-0-12-819822-3.00010-9.

So, H.M., Tse, R.Y.C. and Ganesan, S. (1997) 'Estimating the influence of transport on house prices: evidence from Hong Kong', *Journal of Property Valuation and Investment*, 15(1), pp. 40–47. Available at: https://doi.org/10.1108/14635789710163793.

Song, Z. *et al.* (2019) 'Public transport accessibility and housing value uplift: Evidence from the Docklands light railway in London', *Case Studies on Transport Policy*, 7(3), pp. 607–616. Available at: https://doi.org/10.1016/j.cstp.2019.07.001.

Transport for London (no date) *How many cars are there in London and who owns them?* Available at: https://content.tfl.gov.uk/technical-note-12-how-many-cars-are-there-in-london.pdf.

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

United Nations (2021) *Sustainable transport, sustainable development*. Interagency report for second Global Sustainable Transport Conference. Available at: https://sdgs.un.org/sites/default/files/2021-

10/Transportation%20Report%202021_FullReport_Digital.pdf.

Verseckienė, A., Meškauskas, V. and Batarlienė, N. (2016) 'Urban Public Transport Accessibility for People with Movement Disorders: The Case Study of Vilnius', *Procedia Engineering*, 134, pp. 48–56. Available at: https://doi.org/10.1016/j.proeng.2016.01.038.

Yiu, C.Y. and Wong, S.K. (2005) 'The Effects of Expected Transport Improvements on Housing Prices', *Urban Studies*, 42(1), pp. 113–125. Available at: https://doi.org/10.1080/0042098042000309720.

Zhou, Y. *et al.* (2022) 'Effects of Public Transport Accessibility and Property Attributes on Housing Prices in Polycentric Beijing', *Sustainability*, 14(22), p. 14743. Available at: https://doi.org/10.3390/su142214743.

Appendices

Appendix A: Results of spatial lag models.

Dependent variable:	total access index 2010	Number of observation	4835	
Pseudo R-squared	0.8313			
Spatial Pseudo R-squared	0.5601			
Sigma-square ML	16.42			
Log Likelihood	-13940.752			
AIC	27947.504			
Schwarz criterion	28161.464			
Variable	Coefficient	Std.Error	z-Statistic	Probability
w11Q_w11Q2	-0.2943282	0.1886051	-1.560553	0.1186293
w11Q_w11Q3	-0.1115297	0.2014348	-0.5536762	0.5798005
w11Q_w11Q4	-0.2624611	0.1979052	-1.3261963	0.1847747
m11Q_m11Q2	-0.5373121	0.1979716	-2.7140869	0.0066459
m11Q_m11Q3	-0.873145	0.2136825	-4.0861799	0.0000439
m11Q_m11Q4	-0.807284	0.238212	-3.3889305	0.0007017
m11Q_m11Q5	-0.8646328	0.2678336	-3.2282464	0.0012455
a11Q_a11Q2	0.4787795	0.1960463	2.4421758	0.014599
a11Q_a11Q3	0.5936453	0.2097293	2.8305313	0.0046471
a11Q_a11Q4	1.1127387	0.2215833	5.0217625	0.0000005
a11Q_a11Q5	1.3761049	0.2396199	5.7428656	0
b11Q_b11Q2	0.4834474	0.2175746	2.2219849	0.0262843
b11Q_b11Q3	-0.1048551	0.2593684	-0.4042709	0.6860135
b11Q_b11Q4	-0.0885927	0.2899679	-0.3055257	0.7599658
b11Q_b11Q5	-0.5077377	0.3224986	-1.5743871	0.115398
o11Q_o11Q2	-0.4303526	0.2062539	-2.086518	0.0369317
o11Q_o11Q3	-0.4911074	0.2208644	-2.2235696	0.0261774
o11Q_o11Q4	-0.6929535	0.2283205	-3.0350037	0.0024053
o11Q_o11Q5	-0.910898	0.2337573	-3.8967678	0.0000975
income10Q_income10Q2	1.4964403	0.1980574	7.5555895	0
income10Q_income10Q3	2.3647783	0.2192733	10.7846176	0
income10Q_income10Q4	3.0794588	0.2636108	11.6818394	0
income10Q_income10Q5	3.6508769	0.327021	11.1640432	0
age_quartiles11_ageQ2_11	0.3394202	0.1977035	1.7168143	0.0860131
age_quartiles11_ageQ3_11	0.6185505	0.2107003	2.9356892	0.0033281

age_quartiles11_ageQ4_11	0.5262835	0.2380993	2.210353	0.0270807
age_quartiles11_ageQ5_11	0.5963933	0.2671415	2.2324999	0.0255819
PopdensePerKm11	-0.0000656	0.0000118	-5.575837	0
car_percentage11	-0.1936367	0.0078014	-24.8209044	0
OA_1	0.2560302	0.172215	1.4866889	0.137097
location_outer	1.422672	0.1758598	8.0898094	0
W_total_access_index10	0.8456499	0.0076069	111.1691967	0

Dependent variable:	total access index 2023	Number of observation	4835	
Pseudo R-squared	0.8733			
Spatial Pseudo R-squared	0.5262			
Sigma-square ML	17.391			
Log Likelihood	-14140.004			
AIC	28346.008			
Schwarz criterion	28559.968			
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	10.5298931	0.6262341	16.8146263	0
w21Q_w21Q2	-0.0256601	0.1905588	-0.1346573	0.8928828
w21Q_w21Q3	0.2776962	0.2016469	1.3771408	0.1684687
w21Q_w21Q4	-0.0563115	0.1954431	-0.2881223	0.7732531
m21Q_m21Q2	-0.3713684	0.2014507	-1.8434703	0.0652604
m21Q_m21Q3	-0.5831628	0.2174918	-2.6813094	0.0073335
m21Q_m21Q4	-0.520596	0.235798	-2.2078048	0.0272579
m21Q_m21Q5	-0.9137196	0.2567229	-3.5591669	0.000372
a21Q_a21Q2	0.2728191	0.1952065	1.3975919	0.1622357
a21Q_a21Q3	0.7252691	0.2063088	3.5154546	0.000439
a21Q_a21Q4	1.1427245	0.2239331	5.1029732	0.0000003
a21Q_a21Q5	1.2200305	0.2539473	4.8042667	0.0000016
b21Q_b21Q2	0.2620402	0.2165299	1.2101802	0.2262097
b21Q_b21Q3	-0.4232673	0.2455973	-1.7234201	0.0848126
b21Q_b21Q4	-0.2591059	0.2740687	-0.945405	0.3444521
b21Q_b21Q5	0.0005863	0.3044879	0.0019256	0.9984636
o21Q_o21Q2	-0.8305125	0.2090791	-3.9722402	0.0000712
o21Q_o21Q3	-0.8875265	0.2221904	-3.9944407	0.0000648
o21Q_o21Q4	-0.9067	0.2272215	-3.9903789	0.000066
o21Q_o21Q5	-1.3214152	0.227242	-5.815013	0
income19Q_income19Q2	0.6299577	0.2031095	3.101567	0.001925
income19Q_income19Q3	1.0474097	0.2247613	4.6600974	0.0000032

income19Q_income19Q4	1.6925731	0.2544726	6.6512983	0
income19Q_income19Q5	1.6747198	0.3040584	5.5078883	0
age_quartiles21_ageQ2_21	0.2099944	0.1973399	1.0641256	0.2872718
age_quartiles21_ageQ3_21	0.1775186	0.2106259	0.8428146	0.3993321
age_quartiles21_ageQ4_21	0.0216293	0.2235121	0.0967702	0.9229089
age_quartiles21_ageQ5_21	0.322783	0.2622597	1.2307766	0.2184064
PopdensePerKm21	-0.0000589	0.0000128	-4.6050345	0.0000041
car_percentage21	-0.170359	0.0076532	-22.2599537	0
OA_1	-0.0930536	0.1780103	-0.5227429	0.6011532
location_outer	1.7129237	0.1848941	9.2643501	0
W_total_access_index23	0.8914087	0.0059728	149.2450688	0

Dependent variable:	bus access index 2010	Number of observation	4835	
Pseudo R-squared	0.7596			
Spatial Pseudo R-squared	0.4636			
Sigma-square ML	6.966			
Log Likelihood	-11827.207			
AIC	23720.414			
Schwarz criterion	23934.374			
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	6.6461164	0.383774	17.3177859	0
w11Q_w11Q2	-0.2129744	0.1228529	-1.733573	0.0829939
w11Q_w11Q3	-0.1188133	0.1312004	-0.9055864	0.3651548
w11Q_w11Q4	-0.1148328	0.1288916	-0.8909255	0.3729691
m11Q_m11Q2	-0.3295229	0.1289463	-2.5555056	0.0106034
m11Q_m11Q3	-0.5835752	0.139181	-4.1929224	0.0000275
m11Q_m11Q4	-0.5186884	0.1551558	-3.3430168	0.0008287
m11Q_m11Q5	-0.5564014	0.1744341	-3.1897516	0.001424
a11Q_a11Q2	0.2166679	0.1276671	1.6971313	0.0896718
a11Q_a11Q3	0.2676481	0.1364369	1.9616994	0.0497975
a11Q_a11Q4	0.5351128	0.143821	3.7206869	0.0001987
a11Q_a11Q5	0.5866752	0.1553281	3.7770059	0.0001587
b11Q_b11Q2	0.3395551	0.1416855	2.3965414	0.0165506
b11Q_b11Q3	-0.022374	0.1687351	-0.1325985	0.8945109
b11Q_b11Q4	0.1001758	0.1883273	0.5319239	0.5947787
b11Q_b11Q5	-0.1333304	0.2088288	-0.6384675	0.5231694
o11Q_o11Q2	-0.1853179	0.1343312	-1.3795595	0.1677223
o11Q_o11Q3	-0.3032725	0.1438569	-2.1081546	0.0350176
o11Q_o11Q4	-0.2709249	0.1487134	-1.8217922	0.0684865
o11Q_o11Q5	-0.3816808	0.152337	-2.505503	0.0122277

income10Q_income10Q2	0.9286264	0.1289852	7.1994795	0
income10Q_income10Q3	1.3505072	0.1425529	9.4737245	0
income10Q_income10Q4	1.6498173	0.1710954	9.6426737	0
income10Q_income10Q5	1.7917459	0.2117433	8.4618773	0
age_quartiles11_ageQ2_11	0.198072	0.1287659	1.5382339	0.1239914
age_quartiles11_ageQ3_11	0.3088634	0.1371758	2.2515883	0.0243483
age_quartiles11_ageQ4_11	0.3021723	0.1550598	1.9487464	0.0513257
age_quartiles11_ageQ5_11	0.4267066	0.1740002	2.4523337	0.0141933
PopdensePerKm11	-0.000016	0.0000077	-2.0885688	0.0367466
car_percentage11	-0.1124331	0.0049891	-22.535679	0
OA_1	-0.090811	0.1119113	-0.8114553	0.4171043
location_outer	0.9148639	0.1145423	7.9871303	0
W_bus10	0.8085192	0.009176	88.1127515	0

Dependent variable:	bus access index 2023	Number of observation	4835	
Pseudo R-squared	0.7474			
Spatial Pseudo R-squared	0.4095			
Sigma-square ML	6.858			
Log Likelihood	-11797.661			
AIC	23661.323			
Schwarz criterion	23875.283			
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	5.9465736	0.3944589	15.0752672	0
w21Q_w21Q2	-0.1080763	0.1196876	-0.9029874	0.3665326
w21Q_w21Q3	0.0493184	0.1266397	0.3894389	0.6969515
w21Q_w21Q4	-0.0695638	0.122728	-0.5668128	0.5708414
m21Q_m21Q2	-0.1682439	0.1265077	-1.3299101	0.1835479
m21Q_m21Q3	-0.3197745	0.1365755	-2.3413746	0.0192129
m21Q_m21Q4	-0.4468269	0.148062	-3.0178364	0.0025459
m21Q_m21Q5	-0.4297962	0.1612248	-2.6658198	0.0076801
a21Q_a21Q2	0.0053172	0.1225199	0.0433983	0.9653841
a21Q_a21Q3	0.1517867	0.1289854	1.1767735	0.2392859
a21Q_a21Q4	0.3841484	0.1395569	2.7526301	0.0059119
a21Q_a21Q5	0.3047418	0.1582661	1.9255027	0.0541665
b21Q_b21Q2	0.2498091	0.1357437	1.8402995	0.0657243
b21Q_b21Q3	-0.0139602	0.1538169	-0.0907584	0.9276845
b21Q_b21Q4	0.0708381	0.1713949	0.4133036	0.6793842

b21Q_b21Q5	0.2732971	0.1899255	1.4389699	0.1501591
o21Q_o21Q2	-0.2766372	0.1312868	-2.1071223	0.035107
o21Q_o21Q3	-0.3041759	0.1395075	-2.1803551	0.0292311
o21Q_o21Q4	-0.2996534	0.1427126	-2.0996978	0.0357554
o21Q_o21Q5	-0.4289987	0.1428259	-3.0036472	0.0026676
income19Q_income19Q2	0.5274791	0.1276596	4.1319179	0.000036
income19Q_income19Q3	0.6622225	0.1413326	4.6855613	0.0000028
income19Q_income19Q4	0.9147937	0.1599861	5.7179587	0
income19Q_income19Q5	0.7483214	0.1909865	3.9181898	0.0000892
age_quartiles21_ageQ2_21	0.2745468	0.1240102	2.2139052	0.0268353
age_quartiles21_ageQ3_21	0.2999948	0.132368	2.2663693	0.0234288
age_quartiles21_ageQ4_21	0.1164799	0.1403951	0.8296576	0.4067324
age_quartiles21_ageQ5_21	0.3172024	0.1646878	1.9260827	0.054094
PopdensePerKm21	0.0000018	0.000008	0.2190052	0.826646
car_percentage21	-0.0945874	0.0046963	-20.1407612	0
OA_1	-0.3434526	0.1114235	-3.082406	0.0020533
location_outer	1.0627274	0.1161568	9.149075	0
W_bus23	0.8163678	0.0090277	90.4295185	0

Dependent variable:	tube access index 2010	Number of observation	4835	
Pseudo R-squared	0.8835			
Spatial Pseudo R-squared	0.4573			
Sigma-square ML	2.076			
Log Likelihood	-9074.066			
AIC	18214.132			
Schwarz criterion	18428.092			
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	2.0632566	0.1942654	10.6208114	0
w11Q_w11Q2	-0.0407563	0.0670506	-0.6078436	0.5432912
w11Q_w11Q3	0.0772052	0.0716048	1.0782124	0.280939
w11Q_w11Q4	-0.0576943	0.0703583	-0.8200069	0.4122122
m11Q_m11Q2	-0.1637226	0.0703917	-2.3258792	0.020025
m11Q_m11Q3	-0.1437769	0.0759748	-1.8924279	0.058434
m11Q_m11Q4	-0.1210371	0.0846972	-1.4290565	0.152988
m11Q_m11Q5	-0.2244546	0.0952349	-2.3568525	0.0184306
a11Q_a11Q2	0.0736759	0.0697239	1.0566808	0.2906573
a11Q_a11Q3	0.1669982	0.0747234	2.234885	0.0254249

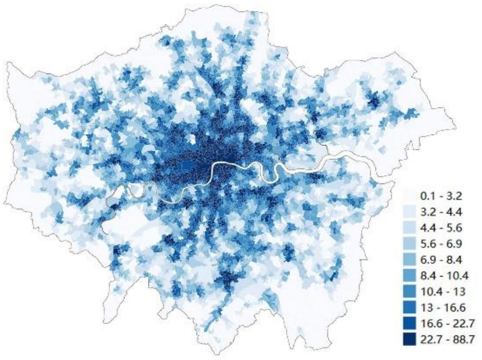
a11Q_a11Q4	0.3430116	0.0792542	4.3279942	0.000015
a11Q_a11Q5	0.5137891	0.0858628	5.9838392	0
b11Q_b11Q2	0.0670379	0.0774487	0.8655779	0.3867217
b11Q_b11Q3	-0.1050311	0.0925176	-1.1352556	0.2562682
b11Q_b11Q4	-0.17091	0.1037141	-1.6478954	0.0993741
b11Q_b11Q5	-0.175862	0.1155008	-1.5226048	0.1278576
o11Q_o11Q2	-0.0970399	0.0733251	-1.3234199	0.1856958
o11Q_o11Q3	-0.1193164	0.0785258	-1.5194546	0.1286481
o11Q_o11Q4	-0.2298494	0.0811744	-2.8315514	0.0046323
o11Q_o11Q5	-0.1725725	0.0831495	-2.0754488	0.037945
income10Q_income10Q2	0.3192941	0.070166	4.5505548	0.0000054
income10Q_income10Q3	0.4690804	0.0772596	6.0714835	0
income10Q_income10Q4	0.6845367	0.0925485	7.3965208	0
income10Q_income10Q5	0.8827987	0.1143581	7.7196006	0
age_quartiles11_ageQ2_11	0.1601716	0.0702581	2.2797598	0.0226219
age_quartiles11_ageQ3_11	0.2548166	0.0748859	3.4027323	0.0006672
age_quartiles11_ageQ4_11	0.1980905	0.0846609	2.3398109	0.0192935
age_quartiles11_ageQ5_11	0.208248	0.0949723	2.1927243	0.0283272
PopdensePerKm11	-0.0000231	0.0000042	-5.5230977	0
car_percentage11	-0.0401675	0.0025668	-15.6490914	0
OA_1	0.0587455	0.0610826	0.9617382	0.3361811
location_outer	0.2994972	0.0625418	4.7887557	0.0000017
W_underground10	0.9343724	0.0048006	194.6347633	0

Dependent variable:	tube access index 2023	Number of observation	4835	
Pseudo R-squared	0.9125			
Spatial Pseudo R-squared	0.4547			
Sigma-square ML	2.821			
Log Likelihood	-9854.458			
AIC	19774.916			
Schwarz criterion	19988.876			
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	2.6187395	0.2380146	11.0024323	0
w21Q_w21Q2	-0.0275065	0.0767441	-0.358419	0.7200298
w21Q_w21Q3	0.1778476	0.081216	2.1898096	0.0285381
w21Q_w21Q4	0.0084699	0.0787087	0.1076106	0.9143046
m21Q_m21Q2	-0.1195181	0.0811391	-1.4730023	0.1407504

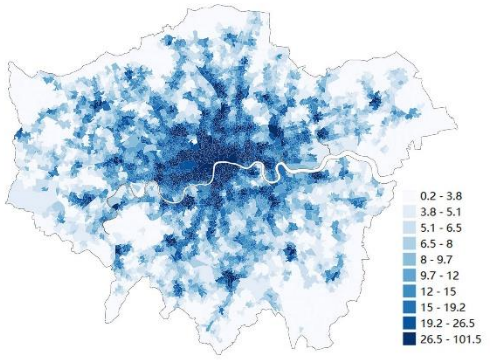
m21Q_m21Q3	-0.1406176	0.0875996	-1.6052313	0.1084429
m21Q_m21Q4	-0.0821728	0.0949564	-0.8653745	0.3868333
m21Q_m21Q5	-0.3755369	0.1034148	-3.6313649	0.0002819
a21Q_a21Q2	0.0905524	0.0787058	1.1505174	0.2499308
a21Q_a21Q3	0.3058569	0.0834157	3.6666593	0.0002457
a21Q_a21Q4	0.4068326	0.0906806	4.4864336	0.0000072
a21Q_a21Q5	0.5383614	0.1027562	5.2392114	0.0000002
b21Q_b21Q2	0.0447401	0.0873747	0.5120486	0.608617
b21Q_b21Q3	-0.2253338	0.0993231	-2.2686952	0.0232869
b21Q_b21Q4	-0.1527862	0.1110503	-1.3758284	0.1688748
b21Q_b21Q5	-0.0220917	0.123684	-0.1786138	0.858241
o21Q_o21Q2	-0.2617925	0.0842121	-3.1087266	0.001879
o21Q_o21Q3	-0.2730578	0.0894962	-3.0510555	0.0022804
o21Q_o21Q4	-0.2956111	0.0915163	-3.2301463	0.0012373
o21Q_o21Q5	-0.3514309	0.0915284	-3.8395813	0.0001232
income19Q_income19Q2	0.095949	0.0817279	1.1740049	0.240393
income19Q_income19Q3	0.2261737	0.0903493	2.5033255	0.0123032
income19Q_income19Q4	0.4713302	0.1021882	4.6123742	0.000004
income19Q_income19Q5	0.5700175	0.1218034	4.6798143	0.0000029
age_quartiles21_ageQ2_21	0.1230817	0.0794518	1.5491369	0.1213488
age_quartiles21_ageQ3_21	0.0190634	0.0847849	0.2248445	0.8221003
age_quartiles21_ageQ4_21	0.0070313	0.0899482	0.0781708	0.9376922
age_quartiles21_ageQ5_21	0.039064	0.1054964	0.3702879	0.711168
PopdensePerKm21	-0.0000326	0.0000051	-6.347711	0
car_percentage21	-0.0422197	0.0028438	-14.8463156	0
OA_1	-0.0215271	0.0715532	-0.3008539	0.7635259
location_outer	0.3639118	0.0743609	4.8938605	0.000001
W_underground23	0.9523717	0.0038668	246.2957808	0

Appendix B: Spatial distributions of public transport accessibility, population density, percentage of white groups, car ownership levels, and income deprivation.

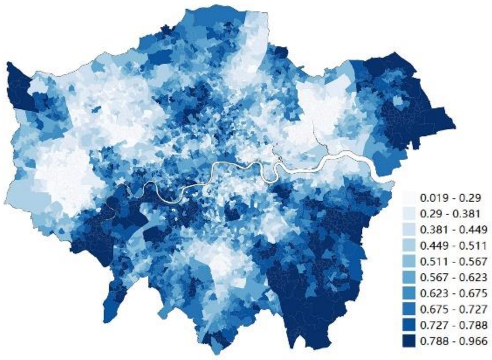
Average Access Index in LSOAs (2010)



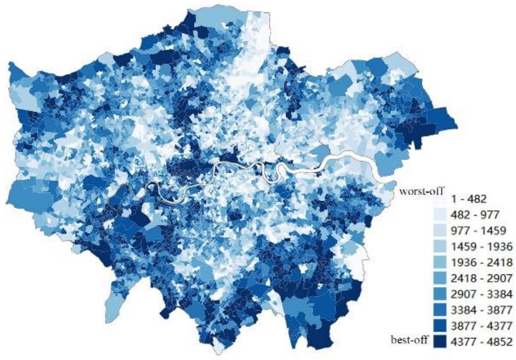
Average Access Index in LSOAs (2023)



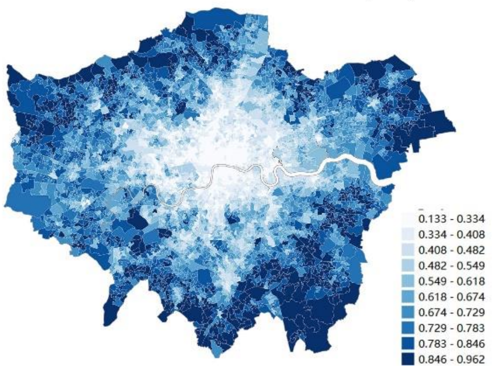
% white groups in LSOAs (2021)



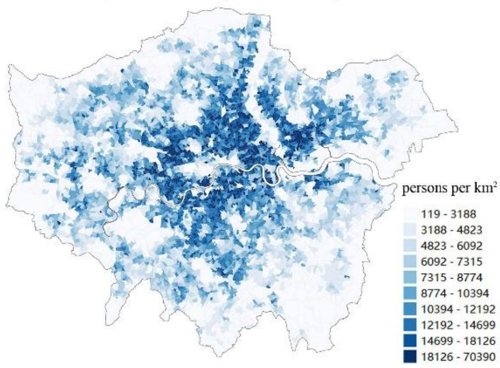
Income deprivation rank in London LSOAs (2019)



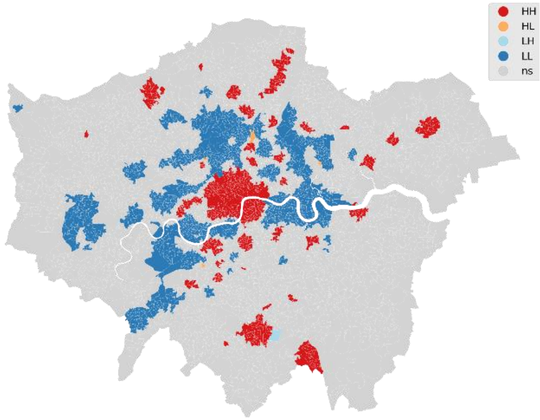
% households with car/van in LSOAs (2021)

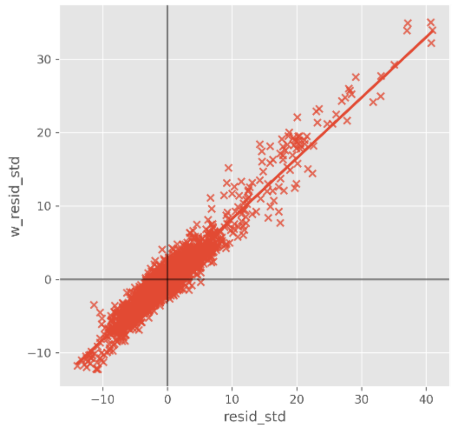


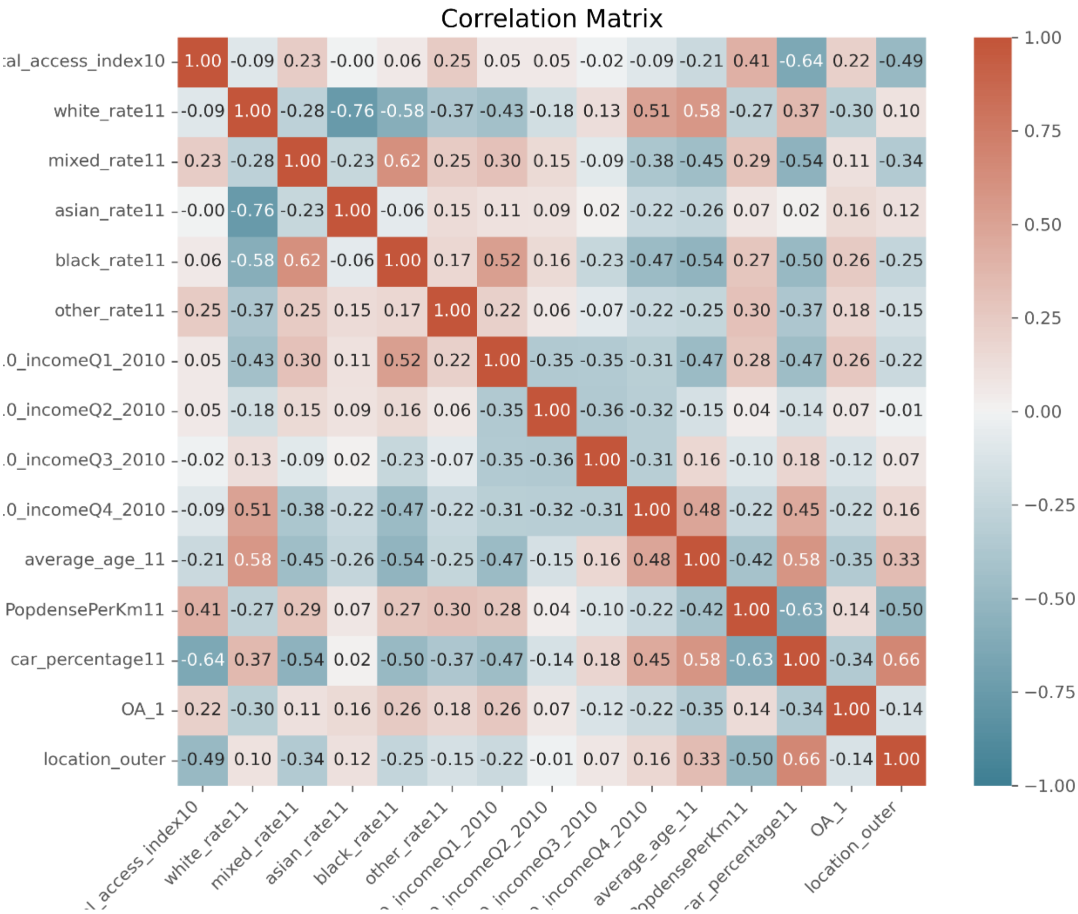
Population density in LSOAs (2021)



Appendix C: Moran's I plot, Local Moran's I map, and correlation matrix of OLS model with total Access Index 2010 and other 2010s variables.







Appendix D: Dissertation supervision meetings.

04 April: discussed about initial ideas about thesis topic and timeline;

10 May: measurement of accessibility, PTAL dataset;

31 May: discussed about correlations of variables, possible results and direction;

09 June: talked about some key references and possible spatial autocorrelation issue;

16 June: questions about the population percentiles, how to make statistical visualisations;

28 June: discussed about the descriptive results, and participation of Mobility Conference. Also discussed about potential confounders;

10 July: final variable selection for spatial models, how to address change after building a weak model. Commented on draft and made some edits;

19 July: how to incorporate with TFL's insights and needs;

02 August: final results interpretation and some strange issues in models;