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

Yuxin Nie[1], Esra Suel[2]

[1, 2] Centre for Advanced Spatial Analysis, University College London, 90 Tottenham Court Road, London, UK, W1T 4TJ

Abstract. Cross-sectional studies have indicated spatial inequalities in public transport accessibility in 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 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.

Keywords: Car-free transport, Accessibility inequalities, Ethnic disparities, Income deprivation, Ten-year change

1 Introduction and background

Public transportation is one of the most important infrastructures for cities [1]. By connecting individuals to education, employment, healthcare, services, and socio-cultural activities [2], public transport becomes the key to providing access to opportunities for all urban residents. However, studies of global cities suggest public transport investment brings up housing prices near the stations [3]–[6], which often leads to gentrification and social exclusion [7]. A similar situation also happens in London, proved by evidence from the research on DLR [8], showing disparities existing in terms of equity and inclusivity. Low-skilled, low-income groups often experience limited accessibility [9], hindering their access to urban services and opportunities [10].

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 [11], but challenges like transit-induced gentrification persist [12].

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 [13]. Spatially, the extent of ethnic diversity across London boroughs varies significantly and disparities in housing are particularly evident, with ethnic minority groups disproportionately concentrated in the most deprived areas of the city. Thus, understanding public transit accessibility of minorities among demographic groups is crucial to grasp the urban dynamics.

This paper aims to contribute to this literature and quantify inequalities in accessibility to public transport in Greater London Area at LSOA (Lower Layer Super Output Areas) level. 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.

2 Methodology and data

2.1 Access Index

We used the Access Index which was extracted from the Public Transport Accessibility Levels (PTAL) dataset (2010 and 2023) from Transport for London (TFL). This measure is being published and actively used by TfL for evaluating planning decisions. It is a measure of how well the place is connected to public transport services [14]. 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 a continuous measure ranging from 0 to over 100. Here, instead of using PTAL categories, we chose the continuous AI value as our measurement of the accessibility of public transportation in the 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 [14].

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

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

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

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

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, 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.

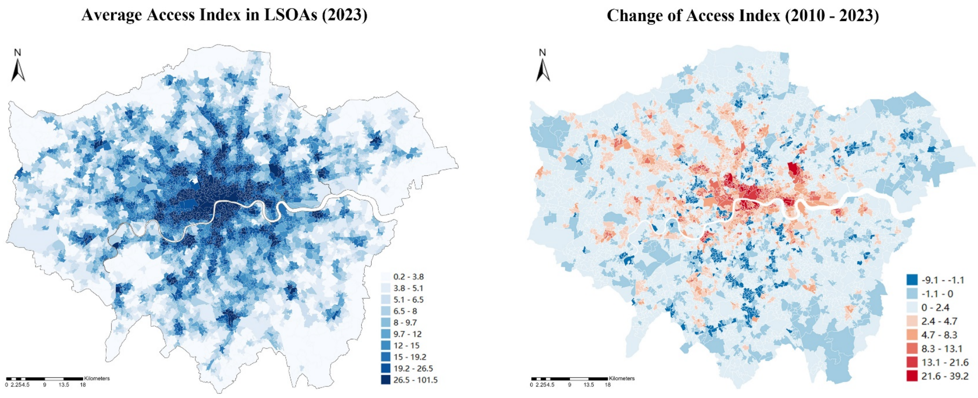

Fig. 1. Spatial distribution of average Access Index at the LSOA level across Greater London Area for 2023; Spatial distribution of change of Access Index from 2010 to 2023 (data source: TFL).

In Figure 1, the access Index shows a decline in some areas due to the 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.

2.2 Neighbourhood demographics

Access Index.

Race and ethnicity are from UK census data in 2011 and 2021 [13]. This study extracted LSOAs within GLA and divided 19 types of ethnicity into 5 categories based on the classification of the UK government and ethnicity question of The Office for National Statistics [13], and calculate the percentage of each ethnic group within LSOAs. The ethnicity category used in this study is: Asian groups (Bangladeshi, Chinese, Indian, Pakistani, Other Asian); Black groups (African, Caribbean, Other Black); Mixed groups (White and Black Caribbean, White and Black African, White and Asian, Other Mixed); White groups (English/Welsh/Scottish/Northern Irish/British, Irish, Gypsy or Irish Traveller, Roma (only 2021), Other White); Other groups (Arab, Any other ethnic group).

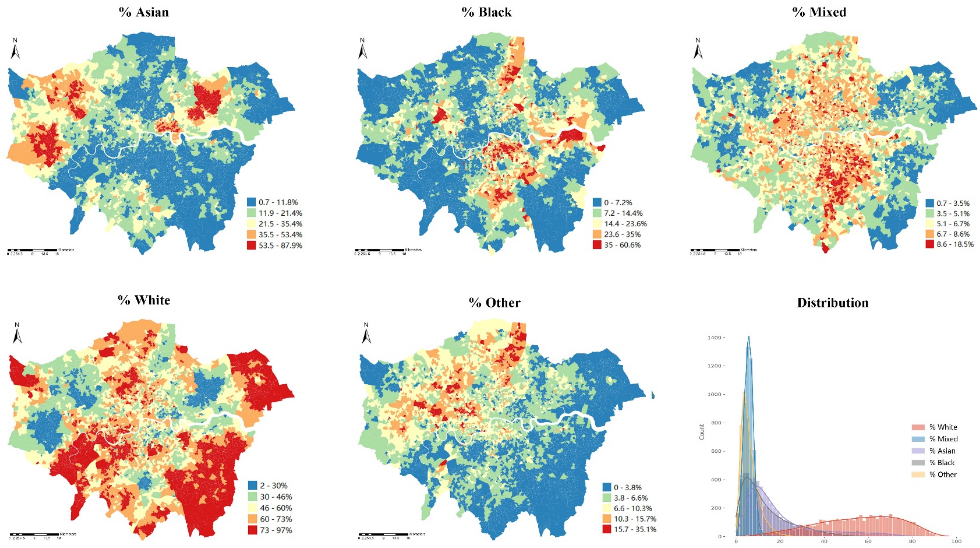

Fig. 2. Spatial distribution of percentages for Asian, Black, Mixed, White, and Other ethnic groups at the LSOA level in 2021. Colour classes have been determined by Fisher-Jenks natural breaks.

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 [15] [16], and divided London LSOAs into 5 quantiles to represent low (Q1), median low (Q2), median (Q3), median high (Q4) and high income groups (Q4) [17].

Age

The age data is also obtained from the census data in terms of LSOA [18]. 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.

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 [19]. 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, monocentric cities are often studied in different circles from inside to outside. For example, Kawabata [20] divided Boston and San Francisco into "central city, inner suburbs and outer suburbs" to make comparison between these three regions. The studies by Smith and Barros [9] [21] divide 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.

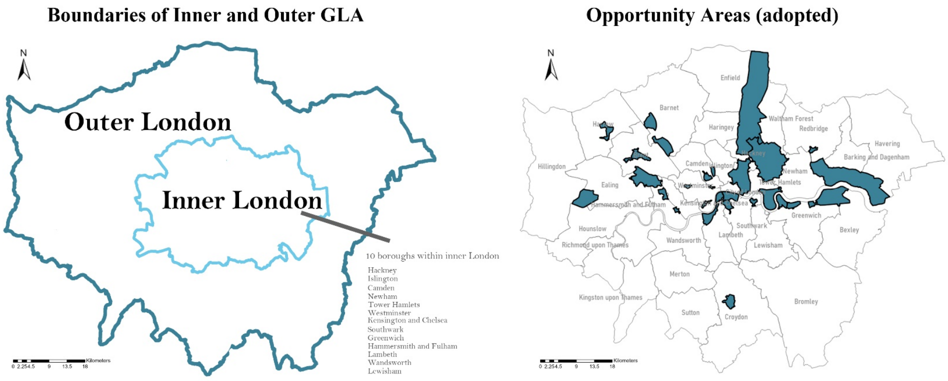

Fig. 3. Boundaries of inner London, outer London of Greater London Area (GLA); Opportunity Areas (adopted ones).

Based on these ideas, this paper sets GLA as the study boundary to capture public transit needs of daily commuters travelling within London and divides the GLA into Inner London and Outer London to quantify the differences between central London and suburbs.

2.4 Potential confounders

Population density

Some literatures found a significant correlation between density distribution and accessibility [22]. 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 [13].

Car ownership

Car ownership has been identified as a significant factor influencing the demand for public transport [23]. On the other hand, research has also shown that affordable and sufficient public transport can deter car ownership [24]. Temporal analysis reveals a complex interrelationship between the two [25]. 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 [26].

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. 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 [27].

2.5 Objectives and methods

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.

In order to select regression model for this study, OLS models were firstly built and the spatial autocorrelation problem was detected by Moran's I. Additionally, the results of Lagrange multiplier (LM) test and the robust LM test indicated that possibility of both spatial lag and spatial error model [28]. To reduce the effect of spatial dependence while select the appropriate spatial model, we built both spatial lag (formula 5) and spatial error (formula 6) models and test their degree of spatial dependence accordingly [29].

$$\mathrm{Y_i} = \alpha + \gamma \sum_j \omega_{ij} \mathrm{Y_i} + \beta \mathrm{X_i} + \epsilon_i \tag{5}$$

$$\mathrm{Y_i} = \alpha + \beta X_i + \epsilon_i \tag{6}$$

$$\epsilon_i = \lambda \sum_j \omega_{ij} \epsilon_i + \mu_i$$

In formula (5) and (6), Y represents average Access Index value for each LSOA i. All the independent variables are included in X. The spatial weighted matrix w, based on the k nearest neighbors, captures the accessibility impact of LSOA i on the neighbouring LSOA j in formula (5) while measures the neighbouring errors in formula (6). λ in the formula (6) represents the coefficient to be estimated for the spatial autocorrelation error term. μ_i

denotes the error term.

The results provided evidence for better performance of spatial lag model. Therefore, we built spatial lag regression models to quantify the associations of Access Index and demographic features for both 2011 and 2021 respectively, as well as make comparison between models in different years to grasp the change happened over the last decade.

3 Statistical analysis

3.1 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 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). 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.

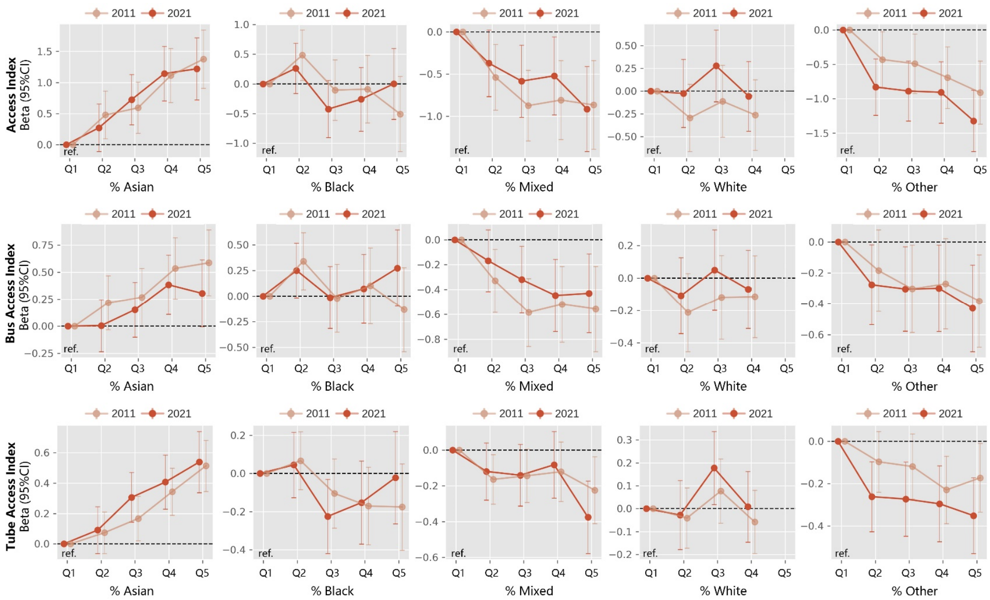

Fig. 4. Associations of total Access Index, bus Access Index, tube Access Index in 2010 and 2023 and five quintiles of percentages of ethnic groups at LSOA level in 2011 and 2021 respectively. Percentages rose from Q1 to Q5. All coefficients were within the 95% Confidence Interval. Q1s were all removed as reference groups.

The relationship between each of the five ethnic groups and public transit accessibility varied. While in terms of different transit modes, different levels of ethnic groups demonstrated similar trends of correlation. Specifically, the Asian groups showed a consistently significant positive correlation with total public transit access index, indicating the advantaged situation of Asian groups in the spatial distribution of accessibility. A comparison between 2011 and 2021 revealed a slight reduction in the advantage of Asian groups in median low (Q2) and hight (Q5) LSOAs. Delving into the breakdown of transport modes, their advantage in bus accessibility during the decade was decreased across all levels. Notably, LSOAs with high-level (Q5) Asian experienced the most significant decline in the bus accessibility advantage.

On the other hand, the Black group presented a more complex scenario. Firstly, areas with median-low (Q2) values experienced a public transport accessibility advantage in both years, despite a declining one. Secondly, the negative correlations seen in Q3 and Q4 levels were mainly contributed by the Black group's tube disadvantage. In the Q5 level with the highest proportion of Black groups, the enhancements in bus accessibility and tube accessibility were both notable. However, the trend of inequality reduction did not extend to other levels of areas.

Counter-intuitively, white groups, often considered advantaged, did not possess an absolute advantage in terms of accessibility to public transport. This was demonstrated by both the total access index and the transit mode breakdown, revealing that only the median level (Q3) LSOAs held a distinct advantage in public transport accessibility while other levels (Q2 and Q4) experienced non-clear or slightly negative relationships.

The mixed group and the other group had both experienced disadvantages over the past decade. In terms of the mixed group, the disadvantage situation in bus enhanced between 2011 and 2021, with all levels of LSOAs showing less shortage. However, in the LSOAs with the highest percentages of the mixed group (Q5), tube accessibility became significantly more disadvantaged, and the gap with other levels of LSOAs further widened. In terms of other groups, as tube accessibility dropped dramatically at all levels, the entire group became more disadvantaged in terms of total accessibility.

In summary, only Asian groups and some levels of black (Q2) and white (Q3) were benefited by total accessibility. Tube accessibility showed improvement in all level Asian, white, Q4 and Q5 black areas. On the other hand, significant declines happened in all areas across the other groups and high level of mixed groups. In terms of the bus access index, Asian, black and white groups had advantages which declined in Asian groups and increased in white groups.

3.2 The Association between Age, Income and Accessibility

This study also divided the LSOAs into five quintiles based on the income deprivation ranking. The most deprived LSOAs were categorised into Q1, representing the lowest income group.

In the spatial lag models, the associations between income levels and accessibility indices were significant at all levels. There was a positive correlation between income and the total access index, with the higher the income level, the more benefits. The LSOAs with the highest income (Q5) exhibited 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 the highest income group. The main contributor to the decline was the bus accessibility, where the highest income Q5 areas showed a significant decrease. Advantages for tube also dropped for all income groups, with the approximately the same amount of decrease.

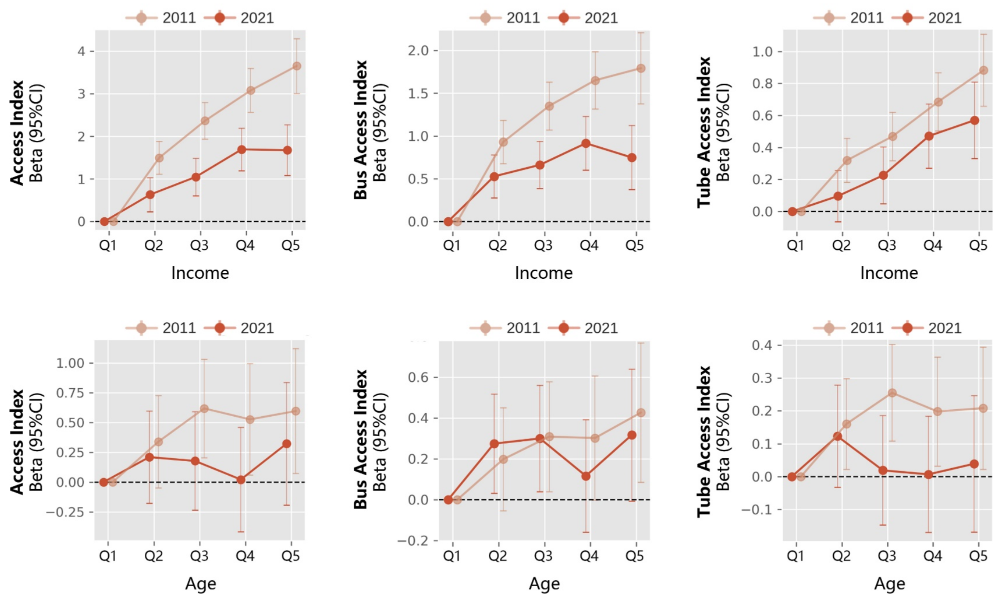

Fig. 5. Associations of total Access Index, bus Access Index, tube Access Index in 2010 and 2023 and five quintiles of percentages of income and age groups at LSOA level in 2011 and 2021 respectively. Percentages rose from Q1 to Q5. All coefficients were within the 95% Confidence Interval.

In terms of age, the 2021 result showed that the all age groups were slightly benefiting from public transport accessibility but the median high aged groups (Q4) did not have obvious pattern.

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 was similar to the total value. Only groups in median low age (Q2) gained more benefits in the past years.

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.

3.3 The Association between change of Accessibility and ethnicity

In order to quantify the relationship between changes in accessibility and demographic characteristics, this part used spatial lag model to measure how demographic variables accounted for changes in accessibility. The model was constructed for the change in the total Access Index and base-year variables (2011) to investigate their relationship.

Table 1. 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—were both changing during the decade, this study controlled for ethnicity distribution in this section. In this case, we assumed that the population did not change between 2011 and 2021, with the public transport accessibility being the only changing variable.

The spatial lag term (weighted change of access) contributed to the overall model at 50%. This means that the changes of Access Index in the neighbouring areas influenced local accessibility changes more than all demographic characteristics, geographic features, and potential confounders combined. However, many of the factors in the model were not significant, thus, their coefficients did not hold strong explanatory value.

Among all the variables, the significance of Asian groups was pronounced. There was more accessibility improvement in Q3, Q4 and Q5 level Asian LSOAs, compared to the area with the fewest Asians. In the previous analyses, we found that in 2011, Asian groups had a significant advantage in accessibility. Combined with this change model, the results presented in Table 1 showed that the advantage of accessibility for areas with large percentages of Asian was further expanding.

Another significant ethnicity, other groups, was in contrast to the Asian groups. Other groups, which faced significant disadvantages, exhibited a negative correlation with accessibility enhancement, which implied new public transport investments further solidified their disadvantaged positions, assuming there was no change in population distribution.

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

4 Conclusion and future work

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?

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 the year 2011 and 2021, this study also indicated temporal changes 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.

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

In terms of age, neighbourhoods with aging groups gained more benefits on overall, bus and tube accessibilities in 2011. Areas with more median low aged people had more advantages in both transport modes in 2021. The advantages of the elderly groups in public transport accessibility had diminished evidently through the years, especially for tube.

However, we noticed the accessibility measure used for this study, also being used by TfL for various planning stages, focused solely on distance to infrastructure and failed to consider travel time, ease of travel, and cost for different transportation options, highlighting the need for further research and improvement in this aspect.

References

[1] C. Aoun, 'The smart city cornerstone: Urban efficiency', *Schneider Electric White Paper*, vol. 1, pp. 1–13, 2013.

[2] A. (Avi) Ceder, 'Urban mobility and public transport: future perspectives and review', *International Journal of Urban Sciences*, vol. 25, no. 4, pp. 455–479, Oct. 2021, doi: 10.1080/12265934.2020.1799846.

[3] H. M. So, R. Y. C. Tse, and S. Ganesan, 'Estimating the influence of transport on house prices: evidence from Hong Kong', *Journal of Property Valuation and Investment*, vol. 15, no. 1, pp. 40–47, Mar. 1997, doi: 10.1108/14635789710163793.

[4] C. Y. Yiu and S. K. Wong, 'The Effects of Expected Transport Improvements on Housing Prices', *Urban Studies*, vol. 42, no. 1, pp. 113–125, Jan. 2005, doi: 10.1080/0042098042000309720.

[5] L. M. Dorantes, A. Paez, and J. M. Vassallo, 'Analysis of House Prices to Assess Economic Impacts of New Public Transport Infrastructure: Madrid Metro Line 12', *Transportation Research*

Record, vol. 2245, no. 1, pp. 131–139, Jan. 2011, doi: 10.3141/2245-16.

[6] Y. Zhou, Y. Tian, C. Y. Jim, X. Liu, J. Luan, and M. Yan, 'Effects of Public Transport Accessibility and Property Attributes on Housing Prices in Polycentric Beijing', *Sustainability*, vol. 14, no. 22, p. 14743, Nov. 2022, doi: 10.3390/su142214743.

[7] M. Padeiro, A. Louro, and N. M. Da Costa, 'Transit-oriented development and gentrification: a systematic review', *Transport Reviews*, vol. 39, no. 6, pp. 733–754, Nov. 2019, doi: 10.1080/01441647.2019.1649316.

[8] Z. Song, M. Cao, T. Han, and R. Hickman, 'Public transport accessibility and housing value uplift: Evidence from the Docklands light railway in London', *Case Studies on Transport Policy*, vol. 7, no. 3, pp. 607–616, Sep. 2019, doi: 10.1016/j.cstp.2019.07.001.

[9] D. A. Smith, Y. Shen, J. Barros, C. Zhong, M. Batty, and M. Giannotti, 'A compact city for the wealthy? Employment accessibility inequalities between occupational classes in the London metropolitan region 2011', *Journal of Transport Geography*, vol. 86, p. 102767, Jun. 2020, doi: 10.1016/j.jtrangeo.2020.102767.

[10] H. Serag El Din, A. Shalaby, H. E. Farouh, and S. A. Elariane, 'Principles of urban quality of life for a neighborhood', *HBRC Journal*, vol. 9, no. 1, pp. 86–92, Apr. 2013, doi: 10.1016/j.hbrcj.2013.02.007.

[11] Greater London Authority, 'Mayor's Transport Strategy', Mar. 2018. [Online]. Available: https://www.london.gov.uk/sites/default/files/mayors-transport-strategy-2018.pdf

[12] M. Lagadic, 'Along the London Overground: Transport Improvements, Gentrification, and Symbolic Ownership along London's Trendiest Line', *City & Community*, vol. 18, no. 3, pp. 1003–1027, Sep. 2019, doi: 10.1111/cico.12414.

[13] Office for National Statistics, 'Ethnic group, England and Wales: Census 2021'. Nov. 2022. [Online]. Available: https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/ethnicity/bulletins/ethnicgroupenglandandwales/census2021

[14] Transport for London and Mayor of London, 'Assessing transport connectivity in London', Apr. 2015.

[15] GOV.UK, 'English indices of deprivation 2010'. Mar. 2011. [Online]. Available: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010

[16] GOV.UK, 'English indices of deprivation 2019'. Sep. 2019. [Online]. Available: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019

[17] J. O. Klompmaker *et al.*, 'Racial, Ethnic, and Socioeconomic Disparities in Multiple Measures of Blue and Green Spaces in the United States', *Environ Health Perspect*, vol. 131, no. 1, p. 017007, Jan. 2023, doi: 10.1289/EHP11164.

[18] Office for National Statistics, 'Age variable: Census 2021'. Aug. 2023. [Online]. Available: https://www.ons.gov.uk/census/census2021dictionary/variablesbytopic/demographyvariablescensus2021/age

[19] Greater London Authority, 'The London Plan', Mar. 2021. [Online]. Available:

https://www.london.gov.uk/sites/default/files/the_london_plan_2021.pdf
[20] M. Kawabata, ‘Spatiotemporal Dimensions of Modal Accessibility Disparity in Boston and San Francisco’, *Environ Plan A*, vol. 41, no. 1, pp. 183–198, Jan. 2009, doi: 10.1068/a4068.
[21] D. A. Smith and J. Barros, ‘Sustainable transport planning and residential segregation at the city scale’, in *Urban Form and Accessibility*, Elsevier, 2021, pp. 27–44. doi: 10.1016/B978-0-12-819822-3.00010-9.
[22] B. J. B. Gultom, A. Affrilyno, D. R. Jati, and A. Andi, ‘FINDING THE CRAMPED SPACE IN A CITY: THE ACCESSIBILITY ASSESSMENT OF PONTIANAK CITY BASED ON THE GRIDDED POPULATION DENSITY’, *JPK*, vol. 10, no. 1, pp. 47–56, Jul. 2022, doi: 10.14710/jpk.10.1.47-56.
[23] J. Holmgren, ‘Meta-analysis of public transport demand’, *Transportation Research Part A: Policy and Practice*, vol. 41, no. 10, pp. 1021–1035, Dec. 2007, doi: 10.1016/j.tra.2007.06.003.
[24] S. Cullinane, ‘The relationship between car ownership and public transport provision: a case study of Hong Kong’, *Transport Policy*, vol. 9, no. 1, pp. 29–39, Jan. 2002, doi: 10.1016/S0967-070X(01)00028-2.
[25] J. Holmgren, ‘The effect of public transport quality on car ownership – A source of wider benefits?’, *Research in Transportation Economics*, vol. 83, p. 100957, Nov. 2020, doi: 10.1016/j.retrec.2020.100957.
[26] Transport for London, ‘How many cars are there in London and who owns them?’ [Online]. Available: https://content.tfl.gov.uk/technical-note-12-how-many-cars-are-there-in-london.pdf
[27] Office for National Statistics, ‘Housing, England and Wales: Census 2021’. Jan. 2023. [Online]. Available:
https://www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/housingenglandandwales/census2021
[28] L. Anselin, ‘Model Selection in Spatial Econometric Models’, in *Spatial Econometrics: Methods and Models*, in Studies in Operational Regional Science, vol. 4. Dordrecht: Springer Netherlands, 1988, pp. 243–252. doi: 10.1007/978-94-015-7799-1_14.
[29] L. Anselin, A. K. Bera, R. Florax, and M. J. Yoon, ‘Simple diagnostic tests for spatial dependence’, *Regional Science and Urban Economics*, vol. 26, no. 1, pp. 77–104, Feb. 1996, doi: 10.1016/0166-0462(95)02111-6.
1.