**Introduction**

Cities support dense social, economic, physical and intellectual networks, which facilitate frequent and complex interactions that in turn drive high levels of productivity, efficiency and innovation (Bettencourt & West, 2010). However, inequality also tends to be greatest in cities, as people embedded in different network locations experience different levels of connectivity to opportunities and resources, which in turn leads to differentiated outcomes among individuals. This can be tangibly seen in how workers who live in different neighbourhoods experience unequal levels of accessibility to jobs (defined as the ability to reach suitable job opportunities within a reasonable travel time or cost via the transport network) (Hansen, 1959), which constrains the job options available to them and shapes their eventual employment outcomes. In some locations, the situation may be more complicated as workers experience both lower accessibility and higher social disadvantage (such as low education, poverty or physical disabilities) (El-Geneidy, et al., 2016).

While the unevenness of job accessibility in cities has been widely studied in the literature, most extant analyses under-explore a highly salient aspect of the actual experience of urban commuting: day-to-day variability in travel times (Katz & Quealy, 2019), which may arise from congestion, varying service schedules and failures of parts of the network. This is because data on transport connectivity with sufficiently fine spatial and temporal resolution to capture the effects of these factors on a day-to-day basis has only recently become freely available, particularly through real-time trip planning platforms. This study leverages on this type of data source to incorporate travel time variability into job accessibility analyses.

In this study, I will analyse the how accessibility to jobs and variability in travel times via public transport affects working-age residents living in different areas under the jurisdiction of the Greater London Authority (GLA), with the aim of identifying areas that are burdened with high social disadvantage, poor accessibility to jobs and/or low travel time reliability. In addition to demonstrating a methodology to productively incorporate the novel angle of travel time variability into accessibility analyses, the findings from this study can also be used to target public transport improvements to increase accessibility to jobs and reliability of travel times to most benefit socially disadvantaged areas.

**Literature Review**

Many studies in urban development and transport geography examine the distribution of accessibility to opportunities in cities. Deboosere & El-Geneidy (2018) identify two main types: those that analyse the “horizontal” *inequality* of accessibility levels across different areas of a city (Levine, 1998; Ford, et al., 2015; Lucas, et al., 2015), and those that analyse the “vertical” *inequity* of the distribution of accessibility levels among population segments (Shen, 1998; Sanchez, 1999; El-Geneidy, et al., 2016; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Deboosere & El-Geneidy, 2018). This corpus clearly shows that it is normal for vast differences in accessibility levels to exist within a city. Also, in poorer cities with less extensive public transport systems, disadvantaged residents are more likely to live in areas with poorer accessibility.

In the context of London, both the UK government (Social Exclusion Unit, 2003) and the GLA (2018) recognise that accessibility is unevenly distributed across space and different population segments. In particular, low accessibility may significantly hinder disadvantaged residents’ access to jobs, healthcare, services, education and leisure, thereby constraining their options, increasing travel burdens, lowering quality of life and entrenching social disadvantage. To make the situation fairer, authorities recommend targeting accessibility improvements to better connect areas with more disadvantaged residents to the opportunities they need.

To assess the extent to which socially disadvantaged populations are more likely to experience poorer accessibility, many researchers use location-based measures of social deprivation, such as neighbourhood average income (Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018) or an index combining multiple dimensions of disadvantage at the local scale (El-Geneidy, et al., 2016; Deboosere & El-Geneidy, 2018). In the UK, the Department for Housing, Communities and Local Government (DHCLG) has developed the Indices of Multiple Deprivation (IMD) to reflect the relative distribution of deprivation among small areas across a wide range of domains, including income, employment, health, education, crime, housing and the living environment (Department for Housing, Communities and Local Government, 2015). In this study, I use the IMD data to capture the relative deprivation of different areas, and will follow the DHCLG guidance to focus on the relative ranking of the areas by IMD index scores, rather than on the raw scores themselves.

Researchers have also developed many metrics to measure accessibility (Geurs & Wee, 2004). The “location-based” type, which regards accessibility as a property of different areas, is widely used for city-level analyses (Shen, 1998; Sanchez, 1999; Kotavaara, et al., 2012; El-Geneidy, et al., 2016; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Deboosere & El-Geneidy, 2018). One simple location-based cumulative potential measure (Geurs & Wee, 2004, p. 133) expresses accessibility as the total number of opportunities (in the case of this study, jobs) that can potentially be reached from each area:

where is the accessibility to jobs for area i, is the number of jobs in area j, is the cost (distance, time and/or fiscal) of travelling from area i to area j, and is an impedance function which decreases the extent to which contributes to as increases.

While measures accessibility as a function of the distributions of jobs and travel costs and is simple to calculate and interpret, a significant drawback is that it does not account for the distribution of the workers who seek jobs (Shen, 1998, p. 348; Hu & Downs, 2019, p. 279); the value for an area will remain the same regardless of the area’s population of workers, but intuitively the accessibility level should decrease as the number of workers increases, to reflect that the limited job supply needs to be shared among a larger demand pool. To address this shortcoming, Shen (1998) proposed an adapted measure that accounts for the number of workers in all areas k (including area i) that can access j and distributes the available jobs from area j to the areas k proportionally by their populations, thus accounting for “competition effects” between workers living in different areas for the same jobs:

where is the number of workers in area k and is the travel cost between areas k and j. Thus, accessibility is a function of 3 components: the distribution of workers (demand), jobs (supply) and travel costs.

Researchers have also increasingly recognised that the spatial distributions of the supply and demand for opportunities and travel costs can all vary significantly over time (Tenkanen, et al., 2016; Järv, et al., 2018; Hu & Downs, 2019). Using geolocated social media or mobile phone data, workplace opening times and public transport schedules, researchers have built time series of these 3 variables over a typical day and calculated accessibility measurements for each area at each time point. Undoubtedly, the increasing availability of fine-grained location and connectivity data will drive further methodological innovations in this direction. However, the extant studies calculate accessibility based on “typical” (mean or ideal) values of these variables at each time point, without accounting for the stochastic distribution of these variables around their typical values that results from variation over time. Thus, extant analyses do not account for the uncertainty that actually exists around accessibility levels.

**Study Design and Data Sources**

This analysis will focus on accessibility to jobs from home locations. Even though not all trips (even during the peak hours) are commutes from homes to work, home-based work commutes are a primary driver of travel demand during peak periods, and thus significantly shape public transport investments that need to be scaled to handle peak demand. In addition, most of the opportunities that people seek (such as education, healthcare or shopping) also provide jobs, so accessibility to jobs will at least somewhat capture accessibility to opportunities in general (Deboosere & El-Geneidy, 2018, p. 56).

The use of location-based cumulative potential accessibility measures requires two choices. The first choice involves which spatial units to use for the analysis. Some studies divide the city in question into a grid of equally-sized squares, in order to minimise distortions in the travel cost calculations due to differences in size and shape between areas (Kotavaara, et al., 2012; Tenkanen, et al., 2016; Järv, et al., 2018; Hu & Downs, 2019). However, aggregating spatial data to these squares requires very fine-grained data (which is unlikely to be publicly available) or additional modelling and assumptions to reproject available data to the squares, at the risk of distorting the data. To avoid this, I follow the majority of extant studies (Shen, 1998; Sanchez, 1999; El-Geneidy, et al., 2016; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Deboosere & El-Geneidy, 2018) in dividing up my study area into pre-existing spatial units, specifically the Middle-layer Super Output Areas (MSOAs) within the GLA boundary. These are spatial data reporting units created by the UK’s Office of National Statistics, and thus provide the ability to seamlessly incorporate a wealth of spatial demographic and economic data from open government databases into my analysis.

The second choice involves which impedance function to use. Many studies use a power or exponential function, such that decreases smoothly as increases, resulting in a “gravity”-based measure where accessibility increases as the “mass” increases and the “distance” decreases (Shen, 1998; Sanchez, 1999; Kotavaara, et al., 2012; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Hu & Downs, 2019). This more accurately reflects the tendency for people to prefer nearer locations with more opportunities to further locations with fewer opportunities, but the resulting raw accessibility values are scores that have no intrinsic meaning and can only be interpreted relative to other scores (El-Geneidy, et al., 2016, p. 304). In contrast, I will follow El-Geneidy et al (2016), Tenkanen et al (2016), Deboosere et al (2018) and Järv et al (2018) to use what Geurs and van Wee (2004) call a “contour” measure, in which:

where X is some travel cost cut-off. This is undoubtedly a distortion of reality, as it treats all locations where as if they were equally attractive and all locations where as if they were totally unattractive. However, the distortion is relatively easy to understand and does not require further assumptions and modelling, and it has the benefit of maintaining the raw accessibility values as simple counts and ratios that can be interpreted directly (Deboosere & El-Geneidy, 2018, p. 55). At any rate, El-Geneidy et al (2016, p. 303) found that contour and gravity-based measures are highly correlated and can be used interchangeably. For the purpose of this study, I will set X to 45min, following TfL’s (2018, p. 224) own analyses.

A key dataset required for this study is the inter-area travel cost matrix. Most extant studies obtain this by compiling a multimodal transport network dataset, incorporating network link speeds, transport service schedules or assumed service frequencies, implementing a routing algorithm, and then finding the shortest route or routes between every pair of areas and calculating the associated costs. See Ford et al (2015, pp. 129-130) for a step-by-step guide. A significant benefit of this approach is that researchers have full knowledge of the underlying network data and routing assumptions used to generate the travel costs. However, the approach requires an extensive data compilation and cleaning effort, is sensitive to the researchers’ choice of routing algorithm, and does not incorporate real-time data on transport service performance.

In contrast, I obtained inter-MSOA travel data from Transport for London’s (TfL’s) Journey Planner (2019). This is a data service that provides the public with guidance on how to travel between any two points in London by non-private transport (i.e. by walking, cycling or motorised public transport like buses or trains, but not by car or taxi), including information on the fare, time, distance and route for up to 6 travel options. This allows me to obtain travel cost data without having to build my own transport network dataset for London, and the results reflect the network and routing assumptions actually used by TfL to assist real travellers in London. Also, crucially, the Journey Planner accounts for real-time disruptions on the transport network; for instance, if a certain rail line is shut down due to a fault, the Journey Planner will not provide options that require travel on that rail line. Thus, this data source is uniquely suited to provide information on travel time variability due to real-time fluctuations in transport service performance.

TfL maintains an application processing interface (API) for the Journey Planner (Transport for London, 2019), which allows for the automated bulk download of travel option data up to a maximum of 300 queries per minute. I used the API to compile the following databases:

1. The travel options for trips between every pair of MSOAs ending at 0830 on 22 March 2019. This constitutes the “baseline” travel option data for all trips for the weekday AM peak, assuming all services run as planned. Due to the API request limit, data collection for all 983 x 983 trips occurred over 1 month.
2. The travel options for trips beginning between 0600 and 0800 every weekday for 50 days between 29 January 2019 and 25 April 2019. This constitutes “real-time” travel option data during the weekday AM peak, reflecting actual day-to-day variability in transport service performance. Because of the API request limit, I only gathered data on trips starting from all 983 MSOAs that end at 7 MSOAs that correspond to 7 key transport nodes evenly spaced across London.

The methodological benefits of using the Journey Planner data are compelling enough to justify its use in this study, but this does impose some constraints on this study’s design. This is because the Journey Planner provides information only for trips that do not involve cars or taxis, and is most reliable for trips within the GLA boundary. As such, my analysis will concentrate only on areas within the GLA boundary and on non-private transport services. TfL data (2018) also show that only 37% of trips within the GLA in 2017 used cars or taxis, while 80% of trips within the GLA boundary were by GLA residents. Nonetheless, I recognise that my results will be distorted by the fact that they omit accessibility by car and taxi, and do not consider areas outside the GLA boundary that can be accessed from London.

**Results**

*Distributions of Jobs, Working-Age Residents, Inter-MSOA Connectivity and IMD Ranks*

As conceptualised in this study, each area’s accessibility to jobs is a function of 3 components: the spatial distributions of working-age population and jobs, and the area-to-area connectivity provided by the public transport system. Figure XX shows the first two components. It is clear that the distribution of jobs is extremely concentrated in the centre of the GLA area, where the City of London, Westminster and Southbank are located. However, there are also smaller concentrations of jobs around some stations in the GLA’s rail and tube network (black lines in the figure), most notably at Canary Wharf. In contrast, the distribution of working-age residents is more even, with lower residential densities in the areas with the most jobs near the centre, higher densities in a ring around the central job-rich core, and decreasing densities as one moves further away from the centre.

The third component, area-to-area connectivity, is stored as a n x n matrix of travel times T between each of the n = 983 MSOAs. The value in each cell of T, , is the minimum time (out of all available options) it takes to travel between the population-weighted centroid of MSOA i and the job-weighted centroid of MSOA j during the AM peak using the baseline database, that is, assuming all services run as scheduled. It is difficult to visualise the entire matrix in a meaningful way, but Figure XX visualises the travel times for all trips originating from the most populous MSOA: Stratford, MSOA ID E02000726, (i.e. the row vector from T where i = E02000726) with the distribution of jobs superimposed. The inset chart shows the total number of jobs that can be reached from Stratford within a certain travel time, i.e. . As the travel time threshold X increases, increases, until all jobs available in the GLA can be reached within X minutes.

The relative deprivation of different MSOAs is also important for us to identify which areas in the GLA area are burdened by both accessibility problems and social disadvantage. Figure XX shows the ranking of each MSOA by IMD scores, together with 3 raw indicators of social disadvantage, namely the modelled mean household income in 2015 (post-housing costs and equivalised for household size), the estimated proportion of households in poverty in 2014, and the unemployment rate among working-age residents in 2017. For all 4 maps, MSOAs are binned into deciles by the distributions of each variable, with more deprived MSOAs visualised in darker shades of red and less deprived ones in darker shades of green. In general, the IMD rankings correspond quite well to the 3 raw indicators of social disadvantage, with a swath of more deprived MSOAs running north-south and another swath running east-west along the northern bank of the River Thames.

*Analysis of Accessibility to Jobs*

In the inset of Figure XX, I plotted the curve of values for Stratford as the travel time cut-off increases. This exercise can be repeated for all MSOAs to yield Figure XX, which plots the value curve for each of the 983 MSOAs. 3 MSOAs are highlighted: Stratford (most populous), the City of London (most jobs) and Waterloo (the MSOA with among the highest value for any given travel time cut-off). The plot reveals 2 points. First, the time needed for residents of each MSOA to be able to reach a certain number of jobs (say half of all available jobs) varies quite widely, from around 45min for residents of the City and Waterloo, to more than 90min for the least well-connected MSOAs. Secondly, the rank-ordering of MSOAs by values does not vary significantly regardless of choice of travel time cut-off; an MSOA that has one of the highest values with a cut-off of 45min will also tend to have one of the highest values with a cut-off of 90min. This reinforces El-Geneidy et al (2016)’s point that contour and gravity-type accessibility measures are largely interchangeable, and indicates that the broad findings from this study are relatively robust against changes in the travel time cut-offs used.

I choose a travel time cut-off of 45min (marked with a red dashed line on Figure XX) to align with TfL’s own accessibility analyses. The value of where each curve intercepts the 45min cut-off line gives a vector of 983 values (one for each MSOA). This is plotted in the left panel of Figure XX, with the values binned into deciles. Clearly, areas in the centre of the GLA area with lots of jobs also have high values. However, the connectivity provided by the public transport network (particularly the rail network, visualised with black lines) extends the region with high values well beyond the City and Westminster, so much so that areas near the edge of the GLA area that are near rail stations may also have relatively high values. However, areas that are not directly served by rail tend to have lower values.

However, as noted above, values improve on as the former account for competition effects from residents of different areas for the same jobs. The right panel of Figure XX visualises the values of each MSOA, which can be straightforwardly interpreted as the following ratio: the number of jobs within 45min AM peak travel time from each MSOA that are allocated to each working-age resident in that MSOA. If jobs, workers and connectivity were all evenly distributed throughout the GLA area, then all the values will equal the ratio of the total number of jobs to the total number of working-age residents, . To express the extent to which actual values deviate from , values are binned into 5 classes: 0 to 50% of (jobs allocated << working-age residents), 50% to 80% of (jobs allocated < working-age residents), 80% to 125% of (jobs allocated ≈ working-age residents, this is a balanced state), 125% to 200% of (jobs allocated > working-age residents), and more than 200% of (jobs allocated >> working-age residents).

From the right panel of Figure XX, we can see that few MSOAs in the GLA area have values close to a balanced state. MSOAs near the centre have too many jobs allocated per working-age resident, while many MSOAs around the outskirts have too few jobs per working-age resident. This is because jobs are mostly concentrated in the centre, while working-age residents are relatively evenly spread out across the GLA, and the public transport system heavily prioritises fast connections to the centre. A notable exception is the relatively more balanced values in the west, where Heathrow Airport provides a significant number of jobs, and connections between Heathrow and areas in the west are relatively good.

*Analysis of Accessibility to Jobs by Sector*

The job distribution data disaggregates jobs by Standard Industrial Classification Codes (SICCs). This allows us to analyse how jobs are allocated to working-age residents by sector. First, I aggregate the SICCs to 6 overarching sectors:

1. Primary and Extractive
2. Industrial
3. Retail, Logistics, Food & Beverage and Hospitality
4. Finance, Insurance, Real Estate, Professional and Administrative Support
5. Public Sector
6. Others

The inset of Figure XX shows the proportion of all jobs in the GLA area that belong to each sector. The finance, insurance, real estate, professional and administrative support sector is the largest in the GLA area, followed by the retail, logistics, food & beverage and hospitality sector and the public sector. Figure XX plots the distribution of jobs in each sector as a dot density map. Industrial jobs are the most evenly spread out across the GLA area, while retail, logistics, food & beverage, hospitality and public sector jobs are somewhat less spread out with significant concentrations in the job-rich centre. Unsurprisingly, finance, insurance, real estate, professional and administrative support jobs are the most concentrated in the centre.

For each MSOA, I calculate values using the job distribution for each sector and plot maps of values per sector in Figure XX. The top left panel of Figure XX reproduces the map in the right panel of Figure XX for reference. Each map uses the same binning convention as the top left panel, except that the values of are now sector-specific. From the maps, we can see that accessibility to industrial jobs is most evenly distributed, while accessibility to public-sector and retail, logistics, food & beverage and hospitality jobs are also relatively evenly distributed albeit with significant over-provision of jobs per working-age population at the centre of the GLA area. In contrast, access to finance, insurance, real estate, professional and administrative support jobs is most unevenly distributed, with large swaths of MSOAs in the south, east and north having almost no jobs from this sector allocated per working-age resident.

When we plot Lorenz curves of the distribution of jobs allocated per sector to the working-age population (lower right panel of Figure XX), we can assess the extent to which the distribution of jobs in each sector contributes to the unevenness in overall accessibility to jobs. The Lorenz curves for the industrial, retail, logistics, food & beverage, hospitality and public sectors are closer to the diagonal than the curve for all jobs, but the curves for the finance, insurance, real estate, professional and administrative services and other sectors are below the curve for all jobs. This indicates that the distributions of the latter two sectors tends to make accessibility to jobs more uneven in the GLA area. In particular, because the finance, insurance, real estate, professional and administrative services sector is the largest in the GLA, the high concentration of jobs in this sector in the centre of the GLA area tends to drive the unevenness in the distribution of accessibility to jobs in the GLA area.

*Identifying Socially Deprived Areas with Poor Accessibility to Jobs*

Ideally, we should improve the public transport network and redistribute jobs and homes such that accessibility to jobs is even throughout the GLA area. However, in order to minimise social inequity, improvements should be prioritised to benefit the neediest areas first (citation). To do this, we need to identify areas which have high social deprivation and poor accessibility to jobs.

To this end, I carry out k-means clustering to classify MSOAs according to their sector-specific values and their IMD ranks, to identify a typology of MSOAs characterised by the number of jobs per sector allocated to each working-age resident and the relative level of deprivation of each area. The results for when k = 6 are presented in Figure XX. The upper left panel visualises the distribution of IMD ranks in each cluster. Cluster 0 is most deprived, while Clusters 1 and 5 tend to be more deprived, and Clusters 2, 3 and 4 tend to be less deprived. The upper right panel visualises the distribution of values for all jobs per cluster. Among the more deprived clusters, Cluster 0 has the lowest values, indicating areas that tend to be most deprived and to have the poorest overall accessibility to jobs. However, Clusters 1 and 5 tend to have values that indicate too many jobs allocated per working-age resident.

The lower left panel of Figure XX displays the distribution of sector-specific values per cluster. This sheds some more light on the job allocation situation for Clusters 1 and 5. Although these clusters tend to have plenty of jobs per working-age resident, most of these jobs are in the finance, insurance, real estate, professional and administrative support sector. Insofar as these sectors tend to require higher qualifications, there may be a skills mismatch between the more socially disadvantaged residents of MSOAs in Clusters 1 and 5 and the jobs that are available to them; in other words, though there may be enough jobs available, the types of jobs available may not match the types of workers available.

In contrast, MSOAs in Clusters 2, 3 and 4 tend to have lower deprivation but also insufficient jobs allocated per working-age resident. Faced with poor accessibility to the jobs they seek via public transport, residents in these MSOAs may be more likely to rely on cars for their commutes. Improving public transport accessibility to jobs for these areas may be a prerequisite to encouraging less car-dependent commute choices for residents of these areas, but the effectiveness of public transport improvements to encourage lower car usage remains in doubt.

# **References**

Bettencourt, L. & West, G., 2010. A unified theory of urban living. *Nature,* 10, Volume 467, pp. 912-913.

Deboosere, R. & El-Geneidy, A., 2018. Evaluating equity and accessibility to jobs by public transport across Canada. *Journal of Transport Geography,* 12, Volume 73, pp. 54-63.

El-Geneidy, A. et al., 2016. The cost of equity: assessing transit accessibility and social disparity using total travel cost. *Transportation Research Part A: Policy and Practice,* 9, Volume 91, pp. 302-316.

Ford, A., Barr, S., Dawson, R. & James, P., 2015. Transport accessibility analysis using GIS: assessing sustainable transport in London. *ISPRS International Journal of Geo-Information,* 1, Volume 4, pp. 124-149.

Geurs, K. T. & Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography,* 6, Volume 12, pp. 127-140.

Greater London Authority, 2018. *Mayor's transport strategy: March 2018.* London: Greater London Authority.

Guzman, L. A. & Oviedo, D., 2018. Accessibility, affordability and equity: assessing `pro-poor' public transport subsidies in Bogotá. *Transport Policy,* 9, Volume 68, pp. 37-51.

Guzman, L. A., Oviedo, D. & Rivera, C., 2017. Assessing equity in transport accessibility to work and study: the Bogotá region. *Journal of Transport Geography,* 1, Volume 58, pp. 236-246.

Hansen, W. G., 1959. How accessibility shapes land use. *Journal of the American Institute of Planners,* 5, Volume 25, pp. 73-76.

Hu, Y. & Downs, J., 2019. Measuring and visualizing place-based space-time job accessibility. *Journal of Transport Geography,* 1, Volume 74, pp. 278-288.

Järv, O. et al., 2018. Dynamic cities: location-based accessibility modelling as a function of time. *Applied Geography.*

Kotavaara, O., Antikainen, H., Marmion, M. & Rusanen, J., 2012. Scale in the effect of accessibility on population change: GIS and a statistical approach to road, air and rail accessibility in Finland, 1990-2008. *The Geographical Journal,* 3, Volume 178, pp. 366-382.

Levine, J., 1998. Rethinking accessibility and jobs-housing balance. *Journal of the American Planning Association,* 6, Volume 64, pp. 133-149.

Lucas, K., 2012. Transport and social exclusion: where are we now?. *Transport Policy,* 3, Volume 20, pp. 105-113.

Lucas, K., Wee, B. & Maat, K., 2015. A method to evaluate equitable accessibility: combining ethical theories and accessibility-based approaches. *Transportation,* 3, Volume 43, pp. 473-490.

Neihaus, M., Galilea, P. & Hurtubia, R., 2016. Accessibility and equity: an approach for wider transport project assessment in Chile. *Research in Transportation Economics.*

Sanchez, T. W., 1999. The connection between public transit and employment: the cases of Portland and Atlanta. *Journal of the American Planning Association,* 9, Volume 65, pp. 284-296.

Shen, Q., 1998. Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. *Environment and Planning B: Planning and Design,* Volume 25, pp. 345-365.

Social Exclusion Unit, 2003. *Making the connections: final report on transport and social exclusion.* London: Office of the Deputy Prime Minister.

Tenkanen, H. et al., 2016. Health research needs more comprehensive accessibility measures: integrating time and transport modes from open data. *International Journal of Health Geographics,* 15(1).

Transport for London, 2018. *Travel in London: report 11.* London: Transport for London.

Transport for London, 2019. *Plan a journey,* London: Transport for London.

Transport for London, 2019. *Transport for London unified API,* London: Transport for London.