Dynamic Accessibility and the Healthcare Ecosystem

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Summary

This paper reports on a recent ESRC-funded investigation of patterns of change in accessibility in the West Midlands using public transport. Accessibility is a term that takes into account both the abilities and possibilities of individuals within a location to access a given location or activity. We assess the implications of accessibility for wider issues of social equity in the study area, defined using geodemographics, and speculate on implications for transport policy.

KEYWORDS: Accessibility dynamics, transport geography, social equity, healthcare

1. Introduction

Accessibility and social inclusion are interlinked issues (Farrington & Farrington, 2005; Lucas, 2012). Public transport provides a necessary, though non-exhaustive way of addressing this issue.

With increases in the capability of computing power it becomes possible to study dynamic accessibility by public transport, taking into account the needs of the individual (Ellegard, Hagerstrand, & Lenntorp, 1977), and also the availability of the activity or destination (opening hours of GP etc.) (Tenkanen, Saarsalmi, Järv, Salonen, & Toivonen, 2016).

Recent studies have looked into dynamic, rather than static, accessibility (Farber, Morang, & Widener, 2014; Fransen et al., 2015; Kujala, Weckström, Mladenović, & Saramäki, 2018; Tenkanen et al., 2016). Previous research has also compared static accessibility over time (El-Geneidy & Levinson, 2007). In this study we will investigate how a metric of dynamic accessibility can be used to measure change over time.

2. Research Design

We will investigate whether the differences in dynamic accessibility of each Output Area (OA) by public transport respond to the "transport need" of the population. We can then assess whether changes in the public transport network unduly effect these populations in a way that decreases their ability to access healthcare. In this specific case we will look at healthcare through the locations of GP surgeries.

As an initial exploration demographic "transport need", we will compare the public transport accessibility findings against the 2011 Output Area Classifications (Gale, Singleton, Bates, & Longley, 2016).

2.1. Data

We process a large number of seasonal timetables for the West Midlands region. These timetables are provided by Transport for West Midlands (TfWM). Due to the format of the timetable data provided

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we develop a novel approach to cleaning and geolocating missing transit stops using the National Public Transport Access Nodes (NaPTAN) dataset. We then use the onebusaway atco cif to convert the data to General Transit Feed Specification (GTFS) converter (*Libraries and utilities for working with public transport data from the UK.*, 2012/2018).

GTFS is a public transport network and timetable format developed by Google (Google, n.d.). In this case it allows us to use the route planning function of OpenTripPlanner (OTP), an open source route planning tool (Open Trip Planner, n.d.).

In order to generate historic accessibility data we link the GTFS data to historic road network data. We downloaded this from Edina Digimap for the specific years to be studied, and then translated this ITN data into Open Street Map format so it could be used by OTP.

2.2. Computational methods

We developed a jython script adapted from Pereira's (2018). This script runs through every OA centroid calculating and saving the trip time to each of the ten nearest GP surgeries every 10 minutes throughout the day from 6am until 11pm. **Figure 1** shows the process of generating this data.

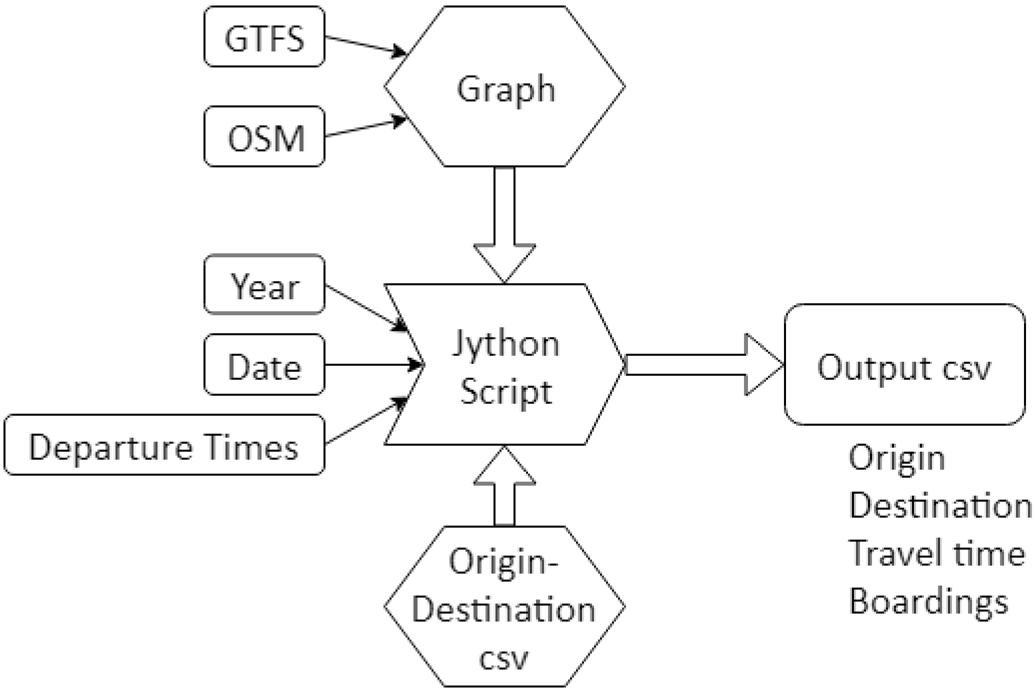

Figure 1 Travel time generation.

This process generated a large dataset of 9,510 OAs with the trip time to the 10 nearest GP surgeries for each given departure time during the time window. This data was used to calculate the accessibility metrics.

Following and adpting the methods set out in Fransen et al. (2015) for each OA centroid we take the mean of the fastest 3 trip times. The mean is then taken of these results for the entire time window. This metric includes the element of choice of GP surgeries, as patients don't necessarily register themselves to the nearest GP (Lewis & Longley, 2012).

3. Results

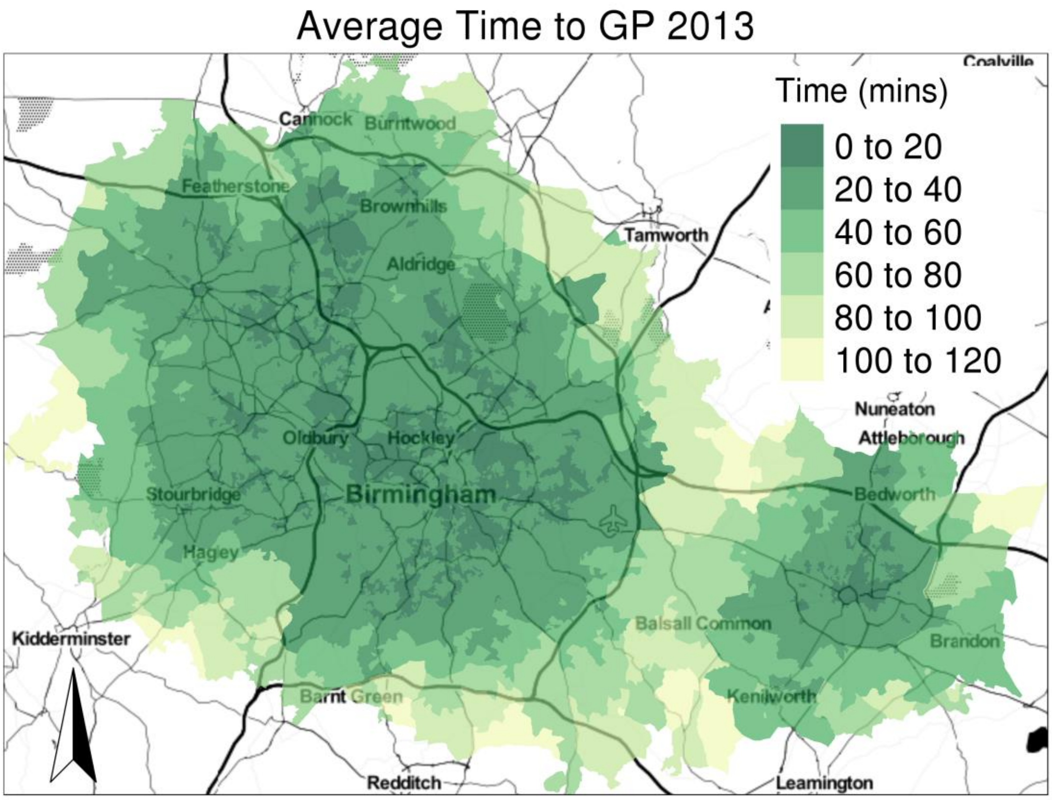

Figure 2 The average time from OA centroid to nearest three GPs. Extent of image 50km.

Figure 2 shows a distinct pattern that generally matches the density of population.

Table 1 The percentage of OAs within average trip time bins in 2013 by OAC.

OAC Super Group	Total No.	0-20 mins	20-40 mins	40 mins plus
1 Rural residents	164	1%	15%	85%
2 Cosmopolitans	203	37%	63%	0%
3 Ethnicity central	294	47%	53%	0%
4 Multicultural metropolitans	3136	42%	58%	0%
5 Urbanites	1237	15%	74%	12%
6 Suburbanites	2044	5%	72%	23%
7 Constrained city dwellers	758	21%	76%	3%
8 Hard-pressed living	1674	16%	74%	9%

In **Table 1**, “Cosmopolitans”, “Ethnicity central”, and “Multicultural metropolitans” areas have lower average trip times. In this example a significant proportion of the OAC Super Group categories “Urbanites”, “Constrained city dwellers” and “Hard-pressed living” are not in the “0-20 mins” bracket. Whilst “Urbanites” are likely to rent privately and have high employment rates, “Constrained city dwellers” are likely to have social housing, younger children and older people, with higher amounts of unpaid care (Gale et al., 2016). This is an element of the demographic for whom public transport could be considered necessary to fulfill the “transport need” of accessing health care.

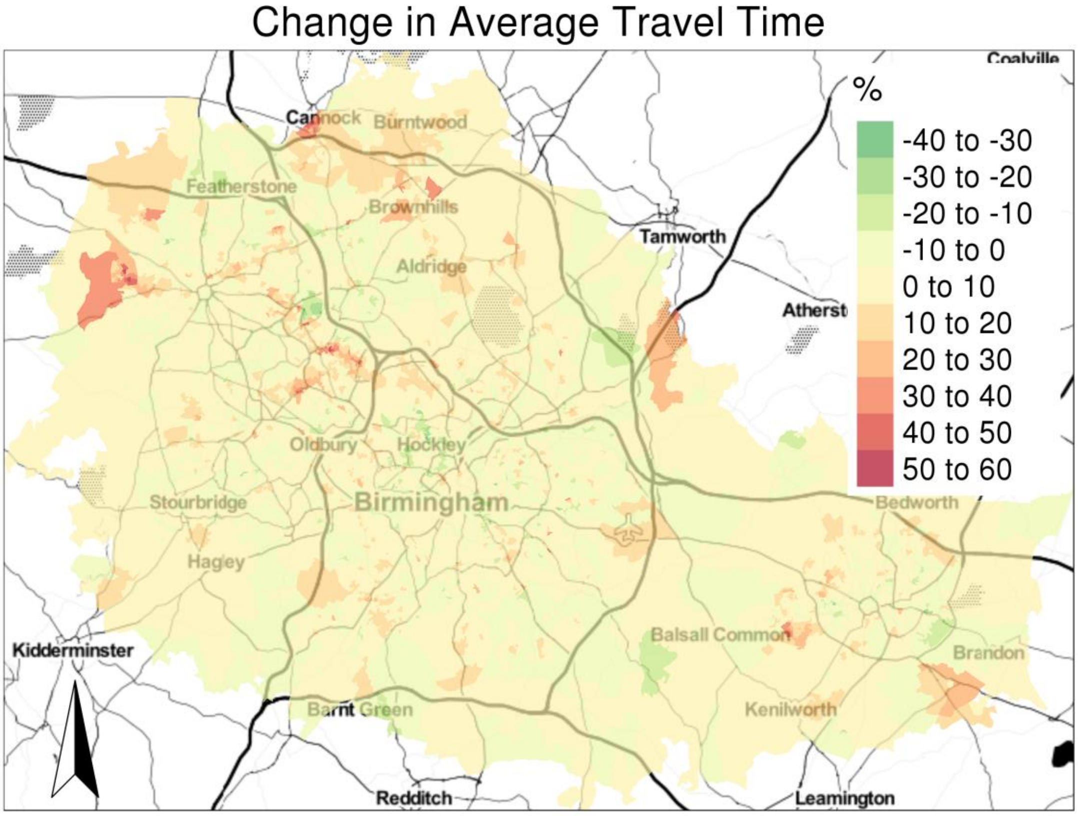

Figure 3 Percentage change in the average travel time from OA centroid to GP surgeries from 2013 to 2016.

Unlike the average travel time, the change in travel time does not follow the same spatial pattern (**Figure 3**). The distribution is quite random, showing little spatial autocorrelation.

Table 2 The percentage of OAC Super Groups in brackets of average travel time change.

OAC Super Group	Total No.	20-50% decrease	5-20% decrease	<5% change	5-20% increase	20-50% increase	>50% increase
1 Rural residents	164	0%	5%	68%	24%	2%	0%
2 Cosmopolitans	203	0%	16%	63%	20%	0%	0%
3 Ethnicity central	294	1%	12%	71%	15%	1%	0%
4 Multicultural metropolitans	3136	1%	10%	67%	21%	1%	0%
5 Urbanites	1237	0%	7%	62%	28%	2%	0%
6 Suburbanites	2044	0%	6%	67%	26%	2%	0%
7 Constrained city dwellers	758	0%	10%	64%	23%	2%	0%
8 Hard-pressed living	1674	0%	7%	67%	23%	2%	0%

Disadvantage is dispersed across the region, presenting a challenge for network design. **Table 2** shows how demographic classifications can be used to assess whether the general decrease in accessibility in the area is unduly effecting parts of the population that need it most. 25% or over of OAs of “Urbanites”, “Suburbanites”, “Constrained city dwellers” and “Hard-pressed living” have significantly increased in average travel time, all greater than the proportion.

4. Discussion

The accessibility by public transport shows a spatial relationship with the density of land use. In **Table 1** there is also shown to be relationship between this accessibility and the demographic factors that make a population more dependent on public transport for mobility. If the overall accessibility by public transport is being reduced, then this type of analysis can be used to asses whether or not proposed changes would unduly affect the sections of the population the rely heaviest upon public transport.

In future research we will look into the actual usage of public transport through Smart Travel Card Transaction data for the area. This will test the positive information against the normative analysis that has been done here.

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References

El-Geneidy, A., & Levinson, D. (2007). Mapping Accessibility Over Time. *Journal of Maps*, *3*(1), 76–87. https://doi.org/10.1080/jom.2007.9710829

Ellegard, K., Hagerstrand, T., & Lenntorp, B. (1977). Activity Organization and the Generation of Daily Travel: Two Future Alternatives. *Economic Geography*, *53*(2), 126. https://doi.org/10.2307/142721

Farber, S., Morang, M. Z., & Widener, M. J. (2014). Temporal variability in transit-based accessibility to supermarkets. *Applied Geography*, *53*, 149–159. https://doi.org/10.1016/j.apgeog.2014.06.012

Farrington, J., & Farrington, C. (2005). Rural accessibility , social inclusion and social justice : towards conceptualisation. *Journal of Transport Geography*, *13*, 1–12. https://doi.org/10.1016/j.jtrangeo.2004.10.002

Fransen, K., Neutens, T., Farber, S., De Maeyer, P., Deruyter, G., & Witlox, F. (2015). Identifying public transport gaps using time-dependent accessibility levels. *Journal of Transport Geography*, *48*, 176–187. https://doi.org/10.1016/j.jtrangeo.2015.09.008

Gale, C. G., Singleton, A. D., Bates, A. G., & Longley, P. A. (2016). Creating the 2011 area classification for output areas (2011 OAC). *Journal of Spatial Information Science*, *12*(12), 1–27. https://doi.org/10.5311/JOSIS.2016.12.232

Google. (n.d.). GTFS Overview | Static Transit. Retrieved 16 January 2019, from https://developers.google.com/transit/gtfs/reference/

Kujala, R., Weckström, C., Mladenović, M. N., & Saramäki, J. (2018). Travel times and transfers in public transport: Comprehensive accessibility analysis based on Pareto-optimal journeys. *Computers, Environment and Urban Systems*, *67*, 41–54. https://doi.org/10.1016/j.compenvurbsys.2017.08.012

Lewis, D. J., & Longley, P. A. (2012). Patterns of Patient Registration with Primary Health Care in the UK National Health Service. *Annals of the Association of American Geographers*, *102*(5), 1135–1145. https://doi.org/10.1080/00045608.2012.657500

Lucas, K. (2012). Transport and social exclusion: Where are we now? *Transport Policy*, *20*, 105–113. https://doi.org/10.1016/j.tranpol.2012.01.013

onebusaway-uk. (2018). Java, OneBusAway. Retrieved from https://github.com/OneBusAway/onebusaway-uk (Original work published 2012)

Open Trip Planner. (n.d.). Open Trip Planner. Retrieved from http://www.opentripplanner.org/

Pereira, R. H. M. (2018). Transport legacy of mega-events and the redistribution of accessibility to urban destinations. *Cities*, (October 2017), 1–16. https://doi.org/10.1016/j.cities.2018.03.013

Tenkanen, H., Saarsalmi, P., Järv, O., Salonen, M., & Toivonen, T. (2016). Health research needs more comprehensive accessibility measures: integrating time and transport modes from open data. *International Journal of Health Geographics*, *15*(1), 23. https://doi.org/10.1186/s12942-016-0052-x

Biographies

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Paul Longley is Professor of Geographic Information Science at University College London, where he also directs the Consumer Data Research Centre. His interests are grouped around socioeconomic applications of GISc, latterly focussing upon geo-temporal demographics.