Accessibility for whom? Applying a data-driven approach to calculate activity-based accessibility metrics.

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Summary

Providing equitable and more sustainable access to basic amenities is key to cutting carbon emissions and increasing social equity in cities. This paper applies a data-driven approach to generate an activity-based accessibility index for British cities. To do so, we employ a two-step approach. Using a self-organising map, we first generate behavioural profiles based on the British Time Use Survey. We then use the resulting clusters to determine the weight of the different amenities in our accessibility index. Our preliminary results seem to provide a promising avenue for applying data-driven methods to generate weighted accessibility scores. Future work will incorporate Census 2021 data in order to better characterise neighbourhoods in terms of both accessibility and their demographic characteristics.

KEYWORDS: Accessibility, Activity-based accessibility, X-minute city, Social equity, Active Travel.

1 Introduction and background

Accessibility is defined as the ease of reaching opportunities (Hansen, 1959). The concept has become increasingly important as a growing number of cities are implementing proximity-based policies to grant wider access to basic opportunities within short walking, cycling, and public transport distances. This is the case of Paris and their 15-minute city model (Moreno et al., 2021), or Copenhagen, which has historically focused on transit-oriented development policies that promote compact and dense residential areas built close to public transport stations (Curtis et al., 2009). At the heart of these policies lays the need to reduce our dependence on private motorised vehicles and, therefore, our carbon emissions (Khomenko et al., 2021; Sicard et al., 2020). Furthermore, evidence has shown us the importance of having access to everyday activities within short-distance trips for democratising well-being standards in our cities (Marquet and Miralles-Guasch, 2015).

Accessibility is heavily influenced by travel and activity patterns (Lee et al., 2017). Literature has widely explored how these behaviours differ across demographic groups. Women, for instance, tend to engage in more multi-purpose trips and use more sustainable means of transport (Han et al.,

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2019; Scheiner and Holz-Rau, 2017; Miralles-Guasch et al., 2016). Older adults, on the other hand, are more prone to walking over any other transport modes and tend to remain local when developing their daily activities (Marquet and Miralles-Guasch, 2015; Vich et al., 2021). The incorporation of all these patterns into accessibility studies is crucial if we want our analyses to be fully inclusive and realistic.

An increasing number of papers have incorporated the equity perspective into accessibility analyses. Calafiore et al. (2022), for example, explore the relationship between socioeconomic status and accessibility, concluding that more deprived areas tend to present lower levels of access. Similar results were obtained by Nicoletti et al. (2022), who, additionally, incorporated amenity weights into their analysis, allowing for generating different accessibility scores based on individual activity preferences. Following Nicoletti et al. (2022)'s work and building on previous studies on activity-based travel behaviours (Victoriano et al., 2020), we propose a data-driven approach to weighting amenities in accessibility analyses. This methodology employs Machine Learning to extract behaviours based on daily activity patterns, and then incorporates these behaviours into an accessibility score. Our preliminary results suggest that there are differences in the spatial distribution of accessibility scores across different activity profiles. Future work will incorporate Census 2021 data in order to better understand the nature of these spatial patterns.

2 Methods and Data

Our methodology is divided into three main steps. First, we generate a set of activity profiles based on an individual's daily behaviours. We then incorporate this information into an accessibility index that takes into account these activity patterns to generate separate accessibility indexes, which reflect the level of access to amenities associated with different lifestyles. Finally, future steps will consist of comparing these results with census data in order to assess whether accessibility scores match the geodemographic patterns of the different neighbourhoods in the city.

2.1 Activity profiles and Self-Organising Maps

Self-organising maps (SOMs) are a dimension reduction methodology with a wide range of applications including clustering or image processing (Kohonen, 2013). SOMs are based on neural networks that convert complex, multidimensional inputs into simpler, two-dimensional outputs in the shape of a grid of neurons. This method assigns observations to the different neurons through an unsupervised competitive learning process. Eventually, once all observations are assigned to a neuron, similar observations will be grouped close to each other (Asan and Ercan, 2012).

Our input data for the SOM are the individual responses to the 2015 British Time Use Survey (Gershuny, 2017), which collects extraordinarily detailed information about the daily activity patterns. We use these data to generate activity profiles based on the proportion of time individuals dedicate to each activity. Following Victoriano et al. (2020), we first classify reported daily behaviours into the activity categories, as presented in Table 1. We then calculate the time each individual dedicated to each category during a regular weekday and use these percentages to feed a SOM algorithm (Wehrens and Buydens, 2007; Wehrens and Kruisselbrink, 2018). The algorithm then classifies each observation based on its similarity to all other observations near it and returns an organised matrix where spatial proximity between individuals implies similarity between them.

Table 1: Activity categories extracted from the British Time Use Survey. We grouped the reported activities related to each category under one of the seven labelled categories and computed the amount of time each individual spent on each activity group.

Category	Description
Care	Time spent helping or assisting others (e.g. accompanying children to school, helping an elderly relative, etc.).
Culture	Time spent at cultural venues.
Education	Time spent at an educational venue or engaged in activities related to study.
Leisure	Time spent doing non-work/study related activities that cannot be labelled as cultural or sports-related (e.g. time spent at restaurants, clubs, pubs, with friends, etc.).
Maintenance	Time spent on housekeeping activities (e.g. cleaning the house, grocery shopping, cooking, etc.).
Sports	Time spent practising sports at sports venues.
Work	Time spent at the workplace.

2.2 Accessibility analysis

Once our activity profiles are defined, we calculate an accessibility score that takes into account each profile's preferences. Similarly to Nicoletti et al. (2022), we estimate our accessibility score as follows:

$$T_i = log(\sum w^c t_i^{1:5}) \tag{1}$$

$$\bar{T_i} = \frac{T_i - min(T_i)}{max(T_i) - min(T_i)} \tag{2}$$

$$\bar{A_i} = 1 - A_i \tag{3}$$

First (Equation 1), we calculate the sum of the average travel time to the closest five amenities of each category. At this point, we incorporate a vector (w^c) with weights for each amenity category, which are derived from the SOM results. We then normalise the values (Equation 2) and generate our final score $\bar{A_i}$ that ranges from low (0) to high (1) accessibility (Equation 3). As origins for our analysis we use the centroids of a hexagonal tessellation we generate covering the whole polygon of the Local Authority District. Amenities used as destinations were obtained from the Ordnance Survey Points of Interest (Ordnance Survey, 2022) (Table 2). To avoid boundary effects (El-Geneidy and Levinson, 2006), we consider all amenities within the Functional Urban Area of the city. We run this analysis for two different transport modes -walking and cycling- and seven study areas -Cambridge, Glasgow, Edinburgh, Liverpool, Milton Keynes, Newcastle upon Tyne, and Nottingham.

Table 2: Selected amenities categorised by activity group. Amenities were filtered and labelled under the below-reported categories. These categories mirror the activity categories defined on the first step of the methodology.

Category	Amenities
Care	Primary schools, pharmacies, GP pratices.
Culture	Museums, art galleries, cinemas, theatres.
Education	Primary schools.
Leisure	Restaurants, pubs, clubs.
Maintenance	Supermarkets, fishmongers, butchers, bakeries, ATMs, post offices.
Sports	Parks, gyms, outdoors sports venues.

3 Preliminary results

Figure 1 shows the activity profiles extracted from the TUS. Combining the self-organising map with a hierarchical clustering algorithm, we obtained 8 clusters -active life, culture fans, housekeepers, leisurers, students, workaholics, working housekeepers, and working leisurers-. For each group, the vertical axis represents the proportion of time spent on each activity. These proportions were used as the weights for each of our amenity categories.

Figure 1: Activity clusters extracted from the British Time Use Survey. The vertical axis represents the proportion of time dedicated to each of the activities listed on the horizontal axis.

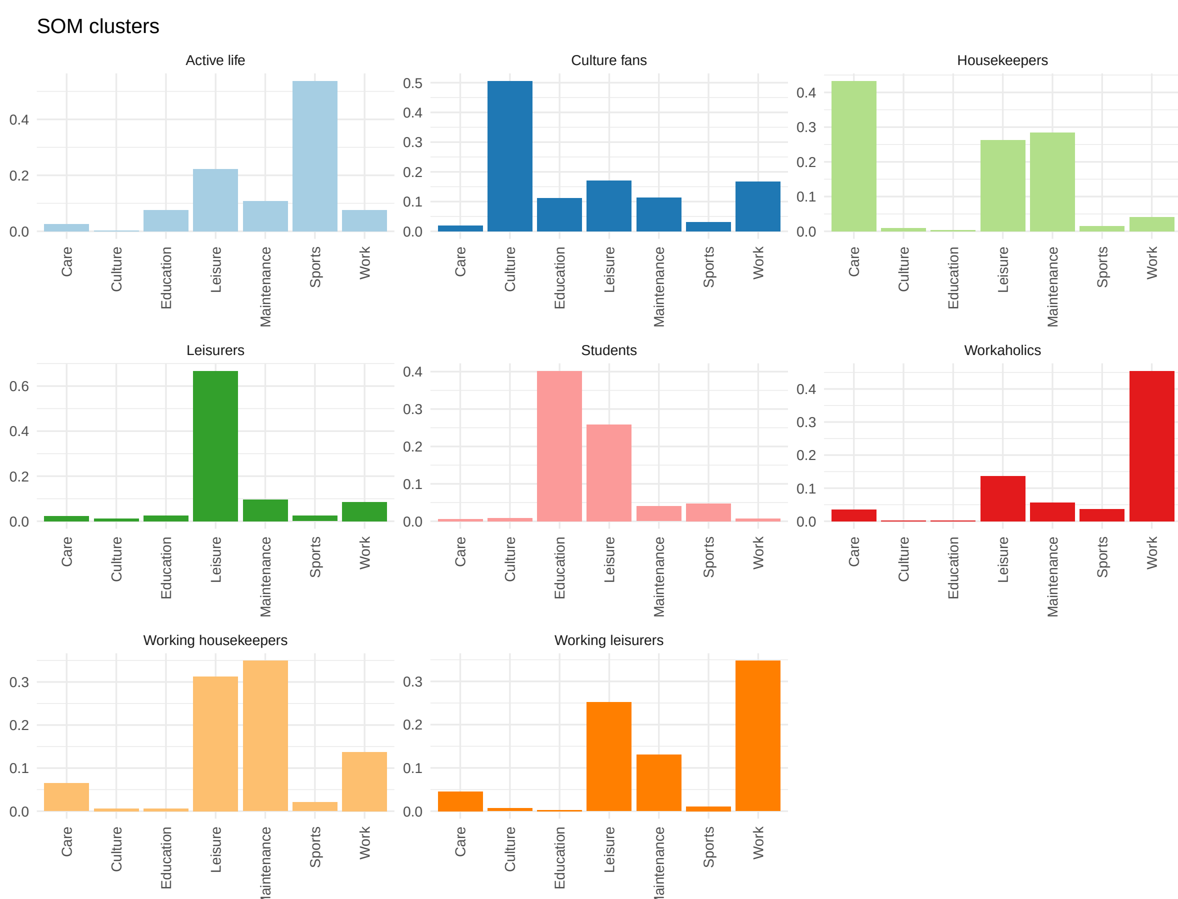
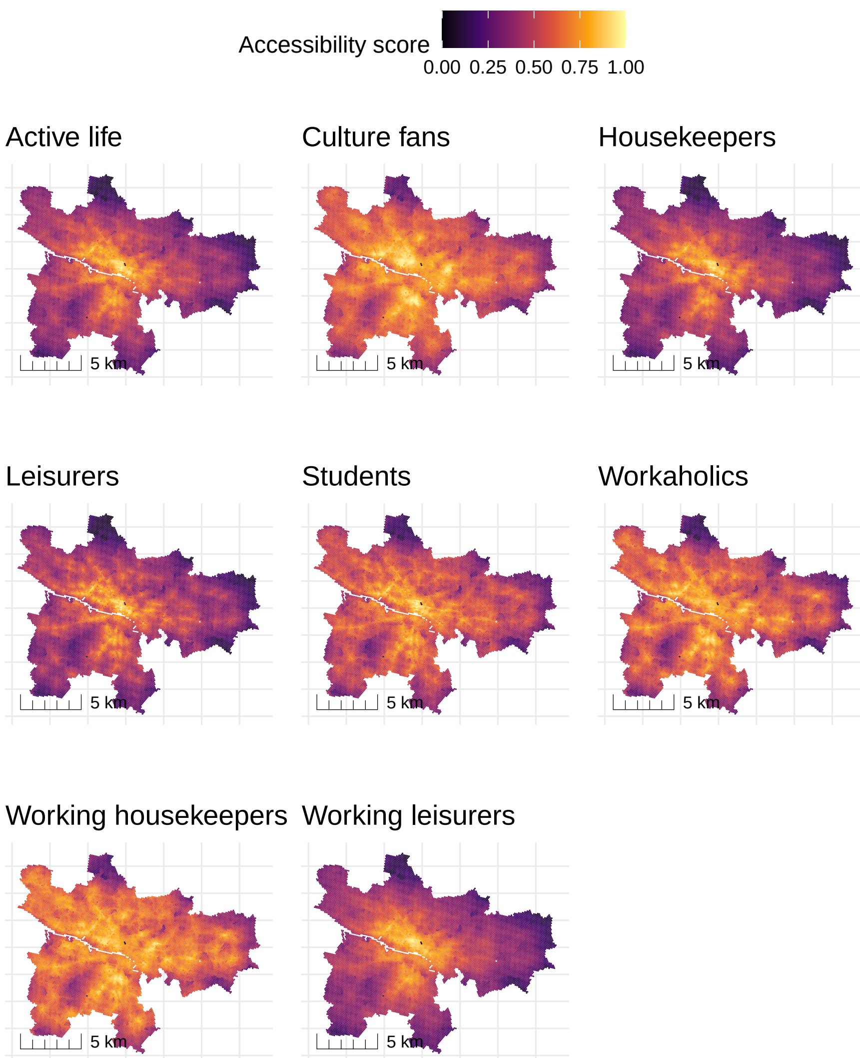


Figure 2 shows the results of our accessibility score for each activity group in the city of Glasgow. Upon further exploration, our methods seem to offer promising results for exploring the spatial differences in access across behavioural profiles. Not surprisingly, the city centre offers the highest levels of access across all categories. However, and more interestingly, we start observing differences in accessibility when we move to areas that are further away from that central district. We observe particularly high access in non-central areas of the city for those that lay within the *working housekeepers*, *culture fans*, and *workaholics* categories.

Figure 2: Accessibility maps for each cluster in Glasgow. We can visually observe the differences in accessibility when incorporating different weigths to different amenities.



4 Discussion and Conclusion

Acknowledging the diversity in activity behaviours is essential for understanding travel patterns in our cities. Accessibility studies have recognised this, and incorporating the equity perspective into the analysis has become almost mandatory. In this study, we propose a data-driven approach to generating accessibility metrics based on travel behaviours. Bringing together methods from the travel behaviour and accessibility literature bodies, we generate a set of accessibility scores that are tailored to different daily activity patterns. The preliminary results presented in this paper are promising. Our activity clustering analysis offers robust results, by using a reproducible methodology applicable to any other context where a time use survey-style data set is available. The methodology seems to offer encouraging results for generating alternative accessibility scores for different behavioural patterns. Future work will incorporate Census 2021 data to better characterise the different neighbourhoods and the link between our weighted accessibility scores and geodemographics.

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6 Biography

Clara Peiret-García is a PhD student at the Geospatial Systems Centre for Doctoral Training, at Newcastle University. Her background is in Applied Economics, and her research interests lie in the areas of accessibility, urban morphology, and sustainable mobility. Prior to starting her PhD she worked as a research assistant in the UK and Spain within projects related to urban studies and sustainability. Since 2021 she is also a member of the Tyndall Centre for Climate Change Research.

Rachel Franklin is a Professor of Geographical Analysis in the Centre for Urban and Regional Development Studies (CURDS) and the School of Geography, Politics and Sociology at Newcastle University, theme lead for Spatial Analytics at Newcastle Data, Co-I for the EPSRC-funded Centre for Doctoral Training (CDT) in Geospatial Systems, and the University Lead for Newcastle for the Alan Turing Institute, where she is also a Fellow.

Alistair Ford is a Lecturer in Geospatial Data Analytics in the Geospatial Engineering group. He have worked as a Principle Investigator, Co-Investigator, and Research Associate on many of multidisciplinary projects, funded by UKRI, the European Commission, and government. He is also a member of the Tyndall Centre for Climate Change Research

Joe Matthews is a Lecturer in Statistical Data Science at Newcastle University, with particular interest in applied statistics for real world problem solving. His research interests span a wide variety of areas where statistical methods can be used to solve real world problems, with a particular historical focus on Bayesian methodology to provide decision support for road safety practitioners.

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